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TESIS DOCTORAL

Systemic Risk and the Impact of Financing Sources on Default Risk

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DEPARTAMENTO DE ECONOMÍA DE LA EMPRESA

Getafe, Juino de 2014

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Getafe, de de

Acknowledgements

I would like to express my deepest gratitude to my supervisor, Professor Peña, Juan Ignacio, who provided insightful and very useful comments and suggestions for my PhD thesis. His guidance helped me during all the time of research and writing of this thesis.

I also would like to thank my colleague and my good friend, Chih-Wei. We met eight years ago, and since then, we have been worked together until now. We finished many papers, and I really enjoy the time we were discussing, arguing, and sharing the happy moments when our paper got accepted in top-tier journals. Without his help, I certainly cannot achieve my current accomplishment in academics, and my PhD thesis.

Finally, I want to thank my parents. They support me all the time since I decided to pursuit my PhD degree in Spain. Without their encouragement, I would never hold what I have now. So, thank you and I love my parents!

Abstract

This thesis studies the systemic risk within the financial sector, and the impact of financing sources on default risk in the corporate sector. The first essay models systemic risk using a common factor that accounts for market-wide shocks and a tail dependence factor that accounts for linkages among extreme stock returns. We show that disregarding the effect of the tail dependence factor leads to a downward bias in the measurement of systemic risk, especially during weak economic times. The second essay explores the mechanism through which a financial crisis affects the default risk of real-economy levered firms using the natural experiment of the 2007−2009 crisis. We find that firms strongly dependent on bank financing suffer higher increases in default risk, than otherwise similar firms with no dependence on bank financing. The third essay empirically examines the effect of rollover risk on default risk. We find that financing sources indeed drive this effect, and in particular our results strongly suggest that being bank dependent magnifies this effect.

Resumen

Esta tesis estudia el riesgo sistémico en el sector financiero , y el impacto de las fuentes de financiación de riesgo de impago en el sector empresarial . El primer ensayo de modelos de riesgo sistémico utilizando un factor común que da cuenta de las perturbaciones a nivel de mercado y un factor de dependencia de cola que da cuenta de los vínculos entre los rendimientos de las acciones extremas. Se demuestra que sin tener en cuenta el efecto del factor de dependencia de cola lleva a un sesgo a la baja en la medición del riesgo sistémico , especialmente durante momentos económicos débiles . El segundo ensayo explora el mecanismo a través del cual una crisis financiera afecta el riesgo de impago de las empresas apalancadas economía real utilizando el experimento natural de la crisis de 2007−2009 . Encontramos que las empresas que dependen en gran medida de la financiación bancaria sufren mayores aumentos en el riesgo de incumplimiento , que las empresas por lo demás similares sin dependencia de la financiación bancaria. El tercer ensayo examina empíricamente el efecto del riesgo de refinanciamiento en el riesgo de impago. Nos encontramos con que las fuentes de financiamiento en coche de hecho este efecto , y en particular, nuestros resultados sugieren fuertemente que siendo magnifica dependiente banco este efecto.

Content

CHAPTER 1

Introduction

Monitoring the whole financial system is required to guarantee its stability. As the 2007–2012 crises highlighted, a key factor that affects the stability of the overall financial system, and the real economy, is the level of systemic risk. Given the importance of systemic risk, the second chapter of this thesis is to model systemic risk. Furthermore, financial sector is interacted with corporate sectors. The third chapter studies the mechanism through which a financial crisis affects the default risk of real-economy levered firms, and how financing sources affects firm default risk. The fourth chapter examines whether rollover risk exacerbates default risk, and whether financing sources drive this effect. I summarize the three chapters as follows.

The chapter 2 in the dissertation is entitled "Measuring Systemic Risk: Common Factor Exposures and Tail Dependence Effects." We model systemic risk using a common factor that accounts for market-wide shocks and a tail dependence factor that accounts for linkages among extreme stock returns. Specifically, our theoretical model allows for firm-specific impacts of infrequent and extreme events. Using data on the four sectors of the U.S. financial industry from 1996 to 2011, we uncover two key empirical findings. First, disregarding the effect of the tail dependence factor leads to a downward bias in the measurement of systemic risk, especially during weak economic times. Second, when these measures serve as leading indicators of the St. Louis Fed Financial Stress Index, measures that include a tail dependence factor offer better forecasting ability than measures based on a common factor only.

The chapter 3 in the dissertation is entitled "Financial Crises, Financing Sources, and Default Risks." We study the mechanism through which a financial crisis affects the default risk of real-economy levered firms using the natural experiment of the 2007−2009 crisis. Using an extensive database of listed non-financial firms in the U.S. market during the period of 2006Q3−2010Q1 and a robust methodology of difference-in-differences matching estimator approach, we find that firms strongly dependent on bank financing suffer higher increases in default risk, than otherwise similar firms with no dependence on bank financing. On the other hand, firms that solely rely on financing from public-debt markets do not experience significant increases in their default risk. Our evidence is consistent with the notion that the bank supply shock theory is the more relevant mechanism explaining the transmission channel of shocks from the financial sector to the real economy which affects to default risk. We also show that bank-dependent firms cannot offset adverse impacts stemming from bank lending supply shocks by substituting bank loans with publicly traded debts.

The chapter 4 in the dissertation is entitled "Do Financing Sources Affect Rollover Risk Effect on Default Risk?" We study industrial firms in the U.S. market over the period between 1986 and 2011 and empirically examine the effect of rollover risk on default risk. We have two main contributions. First, we provide the most comprehensive empirical study of supporting rollover risk effect on default risk by including all levered firms whereas previous studies only used restricted sample. Second we are the first study providing new empirical evidence on to the extent that financing sources drive the effect of rollover risk on default risk. Our results strongly suggest that being bank dependent magnifies the rollover risk effect. Furthermore, our results suggest that poor credit quality, small size, and operating during recession are not necessary of triggering rollover risk effect, and this effect is solely significant for bank dependent firms under these conditions.

I conclude this thesis in the chapter 5.

CHAPTER 2

Measuring Systemic Risk: Common Factor Exposures and Tail Dependence Effects

2.1 Introduction

Multiple published studies document the importance of a stable financial system for not just the financial industry but the real economy as well. Monitoring the whole financial system (not just the banking industry) in turn is required, to guarantee its stability. As the 2007–2012 crises (corporate and sovereign) highlighted, a key factor that affects the stability of the overall financial system, and the real economy, is the level of systemic risk.[1] An accurate measure of this level should be of crucial importance for regulators and investors alike.

In response, extensive literature explores a variety of systemic risk measures (e.g., Bisias *et al.*, 2012). Most measures refer to the aggregate system or individual firm level; in the latter case, systemic risk aggregates can be viewed as the aggregation of financial institutions' risks,[2] which are driven by both common factor exposures to market-wide shocks and additional exposures to other, observed and unobserved factors. A common factor accounts for the systematic component of systemic risk (Das and Uppal, 2004); it cannot capture correlation due to large, infrequent changes (e.g., unexpected failure of a major bank).[3] Therefore, an alternative approach that includes relevant frailty and contagion effects, arising from exposure to unobservable covariates (e.g., common latent factors) is outlined both in

[1] Rajan (2006) highlights the importance of the exposure of the real economy to shocks stemming from the financial sector.

[2] An alternative approximation relies on Lehar's (2005) and Suh's (2012) portfolio approach, which measures systemic risk in the financial sector according to groups of financial firms' risks. Altman and Rijken (2011) similarly assess sovereign default risk by aggregating the Altman's z-scores of non-financial corporations.

[3] Literature on default risks suggests that default times concentrate around periods in which the probability of default of all firms increases. However, this increase cannot be totally, or even partially, explained by firms' common dependence on systematic macroeconomic factors (see Giesecke, 2004; Giesecke and Goldberg, 2004; Elsinger *et al.*, 2006a, 2006b).

Das *et al.* (2007) and Duffie *et al.* (2009). In a frailty setting, the arrival of (bad) news about one firm (extreme negative stock returns) causes a jump in the conditional distribution of hidden covariates and therefore a (negative) jump in any firm's stock returns that depend on the same unobservable covariates.

Unlike previous studies, we use a structural-model approach, rather than a reduced-form approach, and do not make assumptions about the nature of these common factors. Instead, we direct our attention to tail dependence effects that result from simultaneous, extreme equity returns across financial institutions. Furthermore, we focus on the impact of these shocks on systemic risk measures. By adding a correlated jumps factor (as a proxy for tail dependence effects) to the standard Merton (1974) framework,[4] we can address the firm-specific impact of infrequent and extreme events. When a jump occurs, its impact occurs at the same time and in the same direction for all firms (positive or negative), but its size and volatility is specific to each firm. We also refine the methodology proposed by Das and Uppal (2004) to capture joint tail risk behavior over time. Based on our model, we develop three indicators of systemic stress in the financial industry: (1) *DD,* or the average distance-to-default in a given sector; (2) *NoD*, defined as the number of joint defaults in a given sector; and (3) *PIR,* which is the ratio of the price of insurance against financial distress to the aggregate asset value in a given sector. Given that systemic risk is a multidimensional concept, measures of systemic risk should be based on several relevant characteristics (Bisias et al. ,2012) such as size, interconnectedness, substitutability, leverage, herd effects (clone property), correlation with other sectors of the of the financial industry and correlation with the real economy. Our three measures are attractive because they summarize many of these

[4] Adding a correlated jumps factor allows to capture the stylized fact that default correlations may increase when an influential event (e.g. a major bankruptcy), affecting many firms simultaneously, happens. In this vein, Liu, Qi, Shi, and Xie (2013) link default correlation to equity return correlation in the context of the structural framework An alternative view is formulated in Zhou (2001a) which develops a model to compute simultaneous defaults for multiple firms extending the traditional first-passage-time model..

characteristics, in particular: size, leverage, dependence between firms and the whole stock market, and interconnectedness.[5]

In an empirical application, we rely on stock market data, which has a leading role in the price discovery process.[6] Specifically, we focus on the U.S. financial industry and the stock returns of ten largest institutions in four major sectors: depositories, broker-dealers, insurance companies, and others. This concentration on the biggest firms reflects their crucial contribution to systemic risk.[7] The sample period runs from January 1996 to December 2011. The contribution of this article is threefold. First, our model captures the stylized fact that extreme negative co-movements for large financial institutions are stronger and more frequent in bear than in bull markets. Second, disregarding the impact of tail dependence effects leads to underestimates of the systemic risk level, especially during weak economic times. Third, we analyze whether our systemic risk measures offer leading indicators of alternative measures, using a comparison with a model that includes only common factor effects and a measure based on a public financial stress index, namely, the St. Louis Fed Financial Stress Index (STLFSI).[8] The results show that our measures provide extra forecasting power.

This study extends current literature in several ways. First, to compute systemic risk measures, Lehar (2005) and Suh (2012) consider asset correlations and grant equal weight to

[5] In contrast, measures of systematic risk (e.g. CAPM beta) only take into one of these characteristics, namely the correlation between a firm's stock returns and aggregate market stock returns.
[6] This leading role might entail anticipating trends in subsequent failures (Lehar, 2005) or changes in supervisory ratings four quarters in advance (Krainer and Lopez, 2001). Several articles affirm that equity market information leads the credit risk price discovery process. Zhang *et al.* (2009) observe that credit default swaps are sensitive to jumps in equity returns. Previous paper document that the equity market leads both the CDS and bond market in the price discovery process (see Forte and Peña (2009), and Norden and Weber (2009)).
[7] Acharya *et al.* (2010) show that the top six firms in terms of contributions to systemic risk also rank among the top seven in terms of total assets. Patro *et al.* (2013) reveals that daily stock return correlations among large financial institutions track with the level of systemic risk. Pais and Stork (2013) suggest that a high stress level in large banks significantly drives systemic instability.
[8] This index is constructed from 18 weekly data series: 7 interest rate series, 6 yield spreads, and 5 other indicators. We chose the STLFSI for three reasons. It is publicly available, spans the whole sample period, and offers the best indicator among U.S. public financial conditional indexes (Aramonte *et al.* 2013).

both small and large returns. We argue instead that size matters, such that large negative returns must be taken specifically into account to assess the level of systemic risk.[9] Second, traditional jump-diffusion models only allow for individual firm jumps, in terms of both arrival time and size (e.g., Zhou, 2001b), whereas our model assumes a coincident jump arrival time across firms. Third, our study extends Duffie *et al.*'s (2009) approach; both studies model a firm's default risk, considering observed common factors and unobserved frailty effects, but we employ a different modeling framework and deal with different research goals.[10] Fourth, our study extends the results provided by Acharya *et al.* (2010), who present an expected shortfall model, and the *CoVaR* of Adrian and Brunnermeier (2010). Fifth and finally, we expand on Giesecke and Kim's (2011) model, which is based on a reduced-form framework to consider the influences of market-wide and sector-specific risk factors, as well as spillover effects.

Summing up, our contributions are as follows. First, we propose a new structural-form model that includes exposures to both a common factor exposure and a tail dependence effect. This model effectively captures realistic, time-varying characteristics in extreme stock return correlations, overcoming the limitations of standard models of portfolio credit risk that cannot account for the higher default correlations during tough economic times. Second, the set of alternative systemic risk indicators we propose reflects different perspectives on system-wide stability. Third, our empirical results related to the U.S. market during 1996–2011, we establish three key findings: (1) neglecting tail dependence induces a downside bias in systemic risk measures; (2) considering tail dependence improves a model's forecasting

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[9] Bae *et al.* (2003) argue that large negative returns are more influential, and extreme dependence is hidden in traditional correlation measures by the large number of days that present small shocks.

[10] These authors model the frailty effect by including an unobservable macroeconomic variable to determine a firm's default intensity; we consider the frailty effect that results from simultaneous firm-specific shocks in equity markets. Their model is a reduced-form, and ours is a structural-form. Finally, whereas we measure systemic risk in the financial sector, they focus on default clusters among non-financial corporations.

ability; and (3) systemic risk measures based on broker-dealer and insurance sectors lead the public financial stress index on average by a month in advance.

The rest of paper is organized as follows. Section 2, we derive our structural-form model, with both common factor and tail dependence effects. Section 3 contains the methodology and systemic risk measures. After we describe the data in Section 4, we report on the empirical analysis in Section 5. Section 6 concludes.

2.2. The Merton Model with Correlated Jumps

2.2.1. Asset Returns with a Common Factor and Correlated Jumps

This article contributes to emerging literature that proposes bottom-up models of default correlations by modeling the asset value of an individual financial institution, exposed to an observable common factor, tail dependence effects, and an unobservable individual factor. Our model relates to Suh's (2012), which features the common factor with a GARCH process, added to the pure diffusion asset return process. However, we extend this specification by incorporating correlated jumps across individual stocks, which provides a proxy for tail dependence effects. To capture the correlated nature of these jumps, we impose two restrictions. First, we assume that the jump occurs at the same time across all firms. Second, conditional on the jump moving in a given direction (i.e., positive or negative), we assume its size and volatility are firm-specific. With this model, we capture two data features, namely, the correlation between stock returns and a common factor and the infrequent but large changes in stock returns.

Let $V_{j,t}$ and $S_{j,t}$ be firm j's asset value and stock price, respectively, at time t. Although $V_{j,t}$ is not observable, it can be inferred from $S_{j,t}$ on the basis of Merton's model. Then let X_t be the common factor. We consider a discrete-time economy for a period of $[0,T]$, where trading takes place at any of *n + 1* trading points *0*, Δt, $2\Delta t$, …, $n\Delta t$, and $\Delta t = T/n$. We denote the process of the logarithm of asset return ($v_{j,t} \equiv \log\left(V_{j,t}/V_{j,t-1}\right)$) as follows:

$$v_{j,t} = \mu_j + \delta_j\left(x_t - r\right) + w^*_{j,t}, \tag{1}$$

$$w^*_{j,t} = w_{j,t} + Q_j N\left(\Delta t\right) - \bar{Q}_j\lambda, \tag{2}$$

$$w_{j,t} \sim N\left(0, \xi_j\right), \tag{3}$$

where μ_j represents the long-run mean of firm *j*'s log-return, x_t is the log-return of the common factor, *r* is the risk-free interest rate, and $w^*_{j,t}$ indicates exposures to other factors. To capture the impact of correlated jumps across firms' assets, we partition $w^*_{j,t}$ into two components in Equation (2): $w_{j,t}$ is an idiosyncratic factor that follows a multivariate distribution without considering extreme dependence,[11] and $Q_j N\left(\Delta t\right)$ and the adjustment term $-\bar{Q}_j\lambda$, which account for the tail dependence exposure term.[12] With this term, the firm's asset value can jump when its equity price suddenly suffers a large movement, due to the arrival of news. For example, extreme stock returns for one firm may cause a jump in the conditional distribution of hidden covariates, leading to a jump in the stock returns of other firms whose stock returns depend on the same unobservable covariates

In our effort to model large changes in prices occurring at the same time across firms' asset returns, we assume that the arrival of jumps is coincident across all firms' asset returns; that is, $N_j\left(\Delta t\right) = N\left(\Delta t\right)$, such that $N\left(\Delta t\right)$ is the standard Poisson counting process with mean and variance $E\left(N\left(\Delta t\right)\right) = \lambda = Var\left(N\left(\Delta t\right)\right)$. We denote Q_j as a random jump

[11] The specification of $w_{j,t}$ will be described in the following section.

[12] We subtract $\bar{Q}_j\lambda$, where $\bar{Q}_j = E\left[Q_j\right]$, to impose a zero mean Poisson process.

amplitude on the log-return if the Poisson event occurs. Furthermore, we let Q_j and $N\left(\Delta t\right)$ be mutually independent; $Q_j N\left(\Delta t\right)$ is a Poisson random sum of normal random variables. Therefore,

$$Q_j N\left(\Delta t\right) = \sum_{k=1}^{N(\Delta t)} Q_j^{(k)}\left(\Delta t\right), \tag{4}$$

where $Q_j^{(k)}\left(\Delta t\right) \sim N\left(a_j, b_j^{\ 2}\right)$ for $k = 1, 2, \ldots$. In this setting, the distribution of the jump size is asset-specific in its mean and volatility, but the jump arrives at the same time for all firms. For our model, a realization of one Poisson process triggers simultaneous, large movements across multiple companies.

Noting the dynamics of the common factor, we employ a GARCH-type model. Specifically, we follow Heston and Nandi (2000) and model the common factor, under the physical measure P, as

$$x_t = r + \lambda^P h_t + \sqrt{h_t}\varepsilon_t, \tag{5}$$

$$h_t = \omega + \alpha\left(\varepsilon_{t-1} - \gamma\sqrt{h_{t-1}}\right)^2 + \eta h_{t-1}, \tag{6}$$

where *r* is the continuously compounded interest rate for the interval between *t* and $t - \Delta$, ε_t is a standard normal disturbance, and h_t is the conditional variance of the log-return between *t* and $t - \Delta$.[13] The conditional variance of an asset return is time varying, i.e.,

$$Var\left(v_{j,t} \mid \varphi_{t-1}\right) \equiv \sigma_{j,t}^2 = \delta_j^2 h_t + \xi_j + \lambda \hat{b}_j^2, \tag{7}$$

where $\hat{b}_j^2 = a_j^2 + b_j^2$. We provide the derivation in Appendix A.

[13] We make *r* constant for a certain time, using the mean of the risk-free interest rate, that is, the 1-year Treasury constant maturity rate obtained from the U.S. Federal Reserve, divided by 252.

2.2.2. Structural-Form Model with a Factor Jump Diffusion Process

We define equity S under the risk-neutral measure (RN) as a call option with maturity T:

$$S_{j,t} = e^{-r(T-t)} E^{RN}\left[\max\left(V_{j,T} - D_{j,T}, 0\right)\right], \tag{8}$$

such that $S_{j,t}$ denotes the equity price of firm j at time t. Following Duan (1995) we assume that the RN measure satisfies the locally risk-neutral valuation relationship (LRNVR), in which the expected return under the RN measure is the risk-free rate, but the one-period-ahead conditional variance of the return stays the same under the P and RN measures. Adopting the same assumption, Heston and Nandi (2000) show that under the RN measure,

$$x_t = r - \frac{1}{2}h_t + \sqrt{h_t}\varepsilon_t, \tag{9}$$

$$h_t = \omega + \alpha\left(\varepsilon_{t-1} - \left(\gamma + \lambda^P + \frac{1}{2}\right)\sqrt{h_{t-1}}\right)^2 + \eta h_{t-1}. \tag{10}$$

Heston and Nandi (2000) also derive the following conditional generating function of the future common factor:

$$f(\phi) \equiv E_t\left[X_T^{\phi}\right] = X_t^{\phi}\exp\left(A(t;T,\phi) + B(t;T,\phi)h_{t+1}\right), \tag{11}$$

where the coefficients are recursively determined as:

$$A(T;T,\phi) = 0, \tag{12}$$

$$A(t;T,\phi) = A(t+1;T,\phi) + \phi r + B(t+1;T,\phi)\omega - \frac{1}{2}\ln\left(1 - 2\alpha B(t+1;T,\phi)\right), \tag{13}$$

$$B(T;T,\phi) = 0, \tag{14}$$

$$B(t;T,\phi) = \phi\left(\lambda^P + \gamma\right) - \frac{1}{2}\gamma^2 + \eta B(t+1;T,\phi) + \frac{\frac{1}{2}(\phi-\gamma)^2}{1\text{-}2\alpha B(t+1;T,\phi)}. \tag{15}$$

Accordingly, we can derive the conditional generating function for asset values. We start by noting that under the RN measure,

$$\log\frac{V_{j,T}}{V_{j,t}}=\left(r-r\delta_j-\bar{Q}_j\lambda\right)\left(T-t\right)+\delta_j\log\frac{X_T}{X_t}+W_{j,t}^T+Q_jN\left(T\right), \tag{16}$$

where $W_{j,t}^T\equiv w_{j,t+\Delta t}+\ldots+w_{j,t+n\Delta t}$ and $N\left(T\right)=N\left(\Delta t\right)+N\left(2\Delta t\right)+\ldots+N\left(n\Delta t\right)$.[14] Thus we know

$$V_{j,T}^{\phi}=V_{j,t}^{\phi}X_t^{-\delta_j\phi}e^{\phi\left(r-r\delta_j-\bar{Q}_j\lambda\right)\left(T-t\right)+\phi W_{j,t}^T+\phi Q_jN\left(T\right)}X_T^{\delta_j\phi}, \tag{17}$$

and we can derive the conditional generating function for asset values:

$$g_j\left(\phi\right)\equiv E_t\left[V_{j,T}^{\phi}\right]=V_{j,t}^{\phi}X_t^{-\delta_j\phi}e^{\phi\left(r-r\delta_j-\bar{Q}_j\lambda\right)\left(T-t\right)+\phi^2\xi_j\left(T-t\right)/2}f\left(\delta_j\phi\right)E_t\left[e^{\phi Q_jN\left(T\right)}\right], \tag{18}$$

where $E_t\left[e^{\phi Q_jN\left(T\right)}\right]=\exp\left(\lambda\left(T-t\right)\left(\exp\left(a_j\phi+\frac{1}{2}b_j^2\phi^2\right)-1\right)\right)$. Appendix B contains further details. With the assumption that equity is valued as a European call option, we determine the equity valuation formula:

$$\begin{aligned}S_{j,t}&\equiv e^{-r\left(T-t\right)}E_t^{RN}\left[\max\left(V_{j,T}-D_{j,T},0\right)\right]\\&=\frac{1}{2}V_{j,t}+\frac{e^{-r\left(T-t\right)}}{\pi}\int_0^{\infty}\mathrm{Re}\left[\frac{D_{j,T}^{-i\phi}g_j^*\left(i\phi+1\right)}{i\phi}\right]d\phi-D_{j,t}\left(\frac{1}{2}+\frac{1}{\pi}\int_0^{\infty}\mathrm{Re}\left[\frac{D_{j,T}^{-i\phi}g_j^*\left(i\phi\right)}{i\phi}\right]d\phi\right),\end{aligned} \tag{19}$$

where $g_j^*\left(\cdot\right)$ comes from $g_j\left(\cdot\right)$, by replacing λ^P with $-1/2$ and γ with $\gamma^*\left(\equiv\gamma+\lambda^P+1/2\right)$.[15]

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[14] Bates (1991) shows that the difference between the risk-neutral and true parameters of Q_j and N is small, both qualitatively and quantitatively. Thus, we assume $\bar{Q}_j$ obtained under physical probability is the same as that obtained under risk-neutral probability.

[15] The debt is assumed to grow at the risk-free interest rate (Lehar, 2005).

2.2.3. Dynamics of Individual Factors

The unobservable individual factors $w_{j,t}$ may be correlated across firms and over time. In particular, we assume that the vector of individual factors $\mathbf{w}_t \equiv \left[w_{1,t} \dots w_{N,t}\right]'$ follows a multivariate normal distribution with a time-varying covariance matrix,

$$\mathbf{w}_t \sim MVN\left[\mathbf{0}, \mathbf{\Omega}_t\right], \tag{20}$$

where the (*j,k*) element of $\mathbf{\Omega}_t$ is $\xi_{jk,t}$. Then we apply the dynamic conditional correlation (DCC) model (Engle, 2002) to estimate the time-varying asset return correlations of idiosyncratic components for the dynamics of $\mathbf{\Omega}_t$.[16]

To estimate the time-varying covariance matrix $\mathbf{\Omega}_t$, we first use the estimates of $\hat{\Theta}_j$ for institution *j* to estimate the time series $\{V_{j,t}\}$ and $\{v_{j,t}\}$ then obtain the residuals $\hat{w}_{j,t}$, defined as:

$$\hat{w}_{j,t} \equiv v_{j,t} - \left(\hat{\mu}_j + \hat{\delta}_j\left(x_t - r\right) + \left(Q_j N\left(\Delta t\right) - \bar{Q}_j \lambda\right)\right). \tag{21}$$

2.2.4. Estimation

The parameter estimation proceeds in three steps. First, we estimate the common factor parameters $\{\omega, \alpha, \eta, \gamma\}$ in the system of Equations (5) and (6), using the maximum likelihood method, according to the common factor data series. Second, we identify λ, a_j, and b_j, similar to the way Das and Uppal (2004) do.[17] Third, we make two assumptions

[16] In contrast, Suh (2012) features the correlation of individual factors based on diagonal VECH, and Lehar (2005) uses an exponentially weighted moving average scheme. We prefer DCC over other types of multivariate volatility process models (e.g., Brownlees and Engle, 2011) because they are easier to estimate and their parameters have an intuitive interpretation , see Silvennoinen, and Teräsvirta (2009)

[17] The correlated jump intensity derives from stock market information. As in Das and Uppal (2004), we

regarding the estimation of the parameters related to the asset return process of individual institutions. That is, we assume that the maturity of the implied call option is one year, in line with previous literature (e.g., Ronn and Verma, 1986; Lehar, 2005; Suh, 2012). Using the sum of half of the long-term debt plus the short-term debt, we proxy for the debt amount $D_{j,t}$ within the assumed maturity of one year, in accordance with KMV's methodology. For consistency with prior literature (e.g., Duan, 1994, 2000),[18] we used historical returns to estimate the parameters. For one institution at a time, with maximum likelihood methods, we estimated the parameters $\Theta_j = \{\mu_j, \delta_j, \xi_j\}$ for an institution *j*'s asset return. Given institution *j*'s equity price and debt data $\mathbf{S}_j = \left[S_{j,1} \dots S_{j,n}\right]'$, $\mathbf{D}_j = \left[D_{j,1} \dots D_{j,n}\right]'$, and common factor data $\mathbf{x} = \left[x_1 \dots x_n\right]'$, we derive the following log-likelihood function:

$$\begin{aligned}\log L\left(\Theta_j \mid \mathbf{S}_j, \mathbf{x}, \mathbf{D}_j\right) = &-\frac{n-1}{2}\log\left(2\pi\right) - \sum_{t=2}^{n}\log V_{j,t} - \frac{1}{2}\sum_{t=2}^{n}\log\sigma_{j,t}^2 - \sum_{t=2}^{n}\log\left(\frac{\partial S_{j,t}}{\partial V_{j,t}}\right) \\ &-\frac{1}{2}\sum_{t=2}^{n}\frac{\left\{v_{j,t} - \left(\mu_j + \delta_j\left(x_t - r\right) + a_j\lambda - \bar{Q}_j\lambda\right)\right\}^2}{\sigma_{j,t}^2}\end{aligned}, \quad (22)$$

$$\begin{aligned}\frac{\partial S_{j,t}}{\partial V_{j,t}} = \frac{1}{2} + \frac{e^{-r(T-t)}}{\pi}\frac{1}{V_{j,t}}\int_0^\infty \mathrm{Re}\left[\frac{\left(D_{j,t}e^{r(T-t)}\right)^{-i\phi}\left(i\phi+1\right)g_j^*\left(i\phi+1\right)}{i\phi}\right]d\phi - \frac{D_{j,t}}{\pi V_{j,t}} \\ \times\int_0^\infty \mathrm{Re}\left[\left(D_{j,t}e^{r(T-t)}\right)^{-i\phi} g_j^*\left(i\phi\right)\right]d\phi.\end{aligned} \quad (23)$$

Here, $V_{j,t}$ and $\sigma_{j,t}$ provide the solutions to Equations (19) and (7), and $v_{j,t}$ represents the log return of $V_{j,t}$.

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assume a jump diffusion process for the stock return process, and we estimate the parameters by minimizing the root mean square error (RMSE) of two metrics, based on co-skewness and excess kurtosis.

[18] We use the 1-year Treasury constant maturity rate obtained from the U.S. Federal Reserve as the risk-free interest rate.

2.3. Methodology and Systemic Risk Measures

In the following section, we use a model that only accounts for exposure to the common factor as a benchmark. Our model thus nests the benchmark model when $\lambda = 0$. We compute risk indicators from both our proposed and the benchmark model, using the following methodological procedure.

2.3.1. Monte Carlo Simulation

We employ Monte Carlo Simulation because no analytical solution is available for the systemic risk measures over a multi-period time horizon. We draw standard normal random variables and simulate a hypothetical future common factor realization, according to Equations (5) and (6). Next we generate the random variable of correlated jumps by drawing from normal random variables, with a pre-specified mean and standard deviation of firms' jump magnitudes, as well as a Poisson random variable with the pre-specified intensity λ. Finally, we draw multivariate normal random variables as specified by Equation (20) and repeat the process 10,000 times.

2.3.2. Rolling Windows

With a rolling window approach, we consider the extent to which systemic risk measures vary over time, such that we can avoid look-ahead bias. Our one-year rolling window updates every month. Thus, we construct a subsample for month t, using the information from months t, $t - 1$, $t - 2$, …, $t - 11$. We repeat this calculation for month $t + 1$, rolling the sample one month forward. For example, the first subsample, corresponding to December 1996, contains data from January 1996 to December 1996. The sample gets updated by including the following month and discarding the first one, so the second subsample would correspond to January 1997 and contain data from February 1996 to January 1997. Monthly updating effectively balances accuracy against the computational burden.

2.3.3. Systemic Risk Measures

Extant literature offers a plethora of measures of systemic risks (for a review, see Rodriguez-Moreno and Peña, 2013). Such measures should detect at least two kinds of situations and cover two different dimensions. First, some measures warn of the persistent build-up of imbalances within the financial sector (using monthly or quarterly data), whereas others capture the abrupt materialization of systemic risk (daily or intraday data). Second, there should be measures based on the aggregate market level (e.g., interbank rates, stock market, CDS indexes), as well as measures at the individual institution level. No single measure is "best," and alternative measures may be devised according to the objectives of the systemic risk analysis. Our model specifies the dynamics pertaining to both individual institutions and their tail-risk connection, so it supports the calculation of a wide range of systemic risk measures. We develop three alternative indicators.

(1) *DD*: the average distance-to-default in a given sector over a fixed time horizon

*T*he *DD* has been used as proxy for identifying a financial sector's stability. For example, Jokipii and Monnin (2013) and Carlson *et al.* (2011) both use *DD* to signal distress in the financial sector; the former finds a positive link between this measure and real output growth, especially during periods of instability, and the latter suggests that *DD* offers a leading indicator of real economic activity (e.g., bank lending standards and terms).[19] For this study, we compute *DD* using a structural form model, with and without jump effects. In line with the Merton's *DD* framework, it entails the logarithm of asset value minus the logarithm of debt value, divided by the standard deviation of this difference. Formally,

[19] We should point out that our paper's results are based on portfolios of financial institutions. Random measurement errors in the degree of indebtedness of individual institutions tend to be compensated for with a portfolio approach (Saldias, 2013). Moreover, aggregate *DD* is a valuable tool for monitoring risk profiles in the financial sector, despite the modeling assumptions inherent to a Merton-based model (Gropp *et al.*, 2009; Vassalou and Xing, 2004).

$$DD \equiv \frac{E\left[\ln V_T - \ln D_T\right]}{Std\left[\ln V_T - \ln D_T\right]}, \tag{24}$$

where V_T and D_T are the asset's market value and the debt's face value, with maturity T.[20] At a given time point t, for every firm j in a given sector, we compute the daily simulated asset values for the next six months, generated by Monte Carlo simulation. Then we average the difference between the log-asset value and log-debt value and use the result as the numerator; the standard deviation of this difference serves as the denominator. Finally, we compute the average sector value as the weighted-average of all firms in a given sector, with weights based on asset size.[21] The lower the *DD* measure, the higher the level of systemic risk.

(2) *NoD*: the number of joint defaults in a given sector over a fixed time horizon.

If a significant number of financial firms default at the same time, the whole financial system (through asset-fire sale or network contagion) might be severely affected (Lehar, 2005). A financial institution is in default if the market value of its assets falls below of the face value of its debt within the next six months. Thus at a given time point t and for every firm j in a given sector, we compute daily simulated asset values for the next six months, generated by Monte Carlo simulation. Then we compare firm *j's* asset value against the face value of its debt. If the latter is higher than the former, firm j is in default; we compute the number of defaulted firms for each sector. The larger *NoD*, the higher the level of systemic risk.

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[20] The formula of our *DD* measure is consistent with the general form in the Merton model. In a standard Merton *DD*, lnV_T has a mean of $E\left[\ln V_T\right] = \ln V_0 + \left(\mu_V - 0.5\sigma_V^2\right)T$, a standard deviation of $Std\left[\ln V_T\right] = \sigma_V \sqrt{T}$, and a normal distribution. The *DD* in Merton's model is $\left[\left(\ln\left(V_0/D_T\right) + \left(\mu_V - 0.5\sigma_V^2\right)T\right)\Big/\sigma_v\sqrt{T}\right]$. Because D_T is constant, the numerator can be represented as $\ln\left(V_0/D_T\right) + \left(\mu - 0.5_V^2\right)T = E\left[\ln V_T - \ln D_T\right]$, and the denominator can be rewritten as $\sigma_V\sqrt{T} = Std\left(\ln V_T\right) = Std\left[\ln V_T - \ln D_T\right]$.

[21] We assume that the largest institutions should contribute strongly to overall systemic risk in the financial system.

(3) *PIR*: the ratio of the price of insurance against financial distress to the aggregate asset value in a given sector.

This systemic risk measure, proposed by Huang *et al.* (2009), is associated with the idea of assessing the systemic risk of the financial sector by computing the price of the government's contingent insurance against large default losses in the financial sector. With our structural-form model, we consider the amount of financial institution debt that cannot be covered by the institutions themselves, as proxy for this insurance, which we refer to the price of insurance (*PI*). The economic intuition backing this measure is that it proxies the theoretical premium of a risk-based deposit insurance scheme guaranteed by the government (as an insurer of last resort) covering losses exceeding banking sector's total assets.

We measure *PI* by computing a put option value based on the Merton's framework, as Lehar (2005) does. Formally, the price of insurance PI_t^j of a firm *j* at time *t* for a horizon of *T* is $e^{-r(T-t)} \times E\left[\max\left(D_T^j - V_T^j, 0\right)\right]$, where D_T^j is the face value of the firm's debt at time *T*, and V_T^j is the market value of the firm's assets at time *T*. We also consider sector-wide distress, equal to the ratio of the sector's *PI* values to the sector's total asset value over the next six months. We call this risk measure *PIR* and compute it using the formula $PIR_t = \sum_j PI_t^j \Big/ \sum_j Asset_t^j$. Intuitively, the higher the *PIR*, the higher the systemic risk level.

In summary, the indicators rely on intuitive economic interpretations, and we use them to illustrate the temporal trend of overall systemic risk levels. In particular, *DD*, *NoD*, and *PIR* are attractive because they summarize key determinants of systemic risk (firms' size, firms' leverage, dependence between firms and the whole market) as suggested by Acharya *et al.* (2010); they also reflect interconnectedness, as suggested by Cummins and Weiss (2010) and

Jobst (2012).[22] We repeat the Monte Carlo simulation procedure for each month from December 1996 to December 2011, yielding monthly time series for each measure.

2.4. Data

2.4.1. Sample Selection

Our sample comprises large, U.S. financial institutions and spans January 1996 to December 2011. We choose firms with available daily equity prices and quarterly balance sheet information in the CRSP and COMPUSTAT databases.[23] We lag all accounting information by three months to acknowledge reporting delays and substitute for any missing accounting data with the most recent prior observation. The quarterly accounting data is linearly interpolated between quarterly reporting dates at daily frequency. Firms constitute four groups (Acharya *et al.,* 2010; Brownlees and Engle, 2011): depositories, brokers-dealers, insurance companies, and others.[24] We use daily equity returns given that jumps probably appear more clearly in high frequency data.[25] We select the biggest firms based on their book value of total assets at the starting date of each estimation sample for each sector at a given time. Furthermore, the sample only contains firms continuously listed in a prior year, to ensure perfect matches in the number of observations at firm-level and system-level. To avoid survivorship bias, merged or bankrupt entities are also included in the sample, as long as their equity and balance sheet information are available. For each month and in each given sector, the sample includes the ten largest firms. Specific names may change over time because of

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[22] Cummins and Weiss (2010) suggest three primary indicators of systemic risk: (1) size, (2) interconnectedness, and (3) lack of substitutability. Also, Jobst (2012) relates short-term liquidity risk to size and interconnectedness.

[23] We collect information about daily equity prices and returns, as well as outstanding shares, from CRSP. We obtain information about total assets, debt in current liability, long-term debt due in one year, and outstanding shares (if missing in CRSP) from COMPUSTAT.

[24] The four groups are depositories (two-digit standard industrial classification [SIC] code 60); brokers-dealers (four-digit SIC code 6211); insurance companies (two-digit SIC code 63 or 64), and others (two-digit SIC codes 61, 62 except 6211, 65, or 67). We assigned Goldman Sachs to the broker-dealers group, despite its SIC code of 6282, following Acharya *et al.* (2010).

[25] Lehar (2005) and Suh (2012) use lower frequency data (monthly and weekly).

bankruptcies, mergers, or other reasons. Our sample contains 25 depositories, 24 broker-dealers, 22 insurance companies, and 31 other firms. For depositories, broker-dealers, and others, the average number of changes in the identities of the top ten each month is roughly 0.2, or 2.5 per year. For insurance companies, the average is 1 firm per year. In addition to usual mergers and acquisitions,[26] the reasons for these changes relate to financial distress or bankruptcy (e.g., filing for Chapters 7 or 11). The numbers of bankrupt firms across sectors are as follows: 1 of 25 depositories; 1 of 24 broker-dealers; 0 of 22 insurance companies; and 4 of 31 others.[27]

2.4.2. Monthly-Interval Observations

By moving the estimation window month by month, we obtain time-varying estimated parameters and risk measures at the end of each month, from December 1996 to December 2011. This sample contains 181 monthly observations for each parameter and measure. Appendix C provides descriptions of the firms in the empirical application. We compute SIZE and LVG (leverage), both at firm and sector-level, at time *t*. The former is the logarithm of the book value of total assets (firm-level) and the logarithm of the summation of all firms in a sector (sector-level); the latter is the quasi-market value of assets, divided by the market value of equity (firm-level) and the weighted average leverage (sector-level), with weights based on market equity.[28]

Figure 1 shows the annual returns across sectors and for the CRSP value-weighted index, which we use to capture the common factor. The sector-level annual returns, ending at month

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[26] For example, Bear Stearns was acquired by JPMorgan Chase in 2008.

[27] Bankrupt firms are Washington Mutual Inc., Lehman Brothers Holdings Inc., Finova Group Inc., MF Global Holdings Ltd., New Century Financial Corp., and Thornburg Mortgage Inc.

[28] Following Acharya *et al.* (2010), LVG is the standard approximation of leverage, where quasi-market value of assets is obtained from the book value of assets, minus the book value of equity and plus the market value of equity.

t for sector k, can be calculated by $r_{k,t} = \sum_{j=1}^{10} w_{j,k,t} \times r_{j,k,t}$, where $r_{j,k,t}$ is firm j's annual return, and $w_{j,k,t}$ is the weight based on market equity for firm j at the end of month t.

We observe a similar pattern across industries. All sectors show positive performance from 1996 until the end of 1998, when the LTCM crisis occurred. Recovery was slow until the bursting of the dot.com bubble in March 2000. Then a subperiod, until 2003, featured momentum toward recovery. Between mid-2005 and mid-2007, all sectors indicated positive performance, until distress symptoms appeared around July 2007, at the start of the subprime crisis. The market bottomed around March 2009, with a strong rebound in mid-2009. The market plunge around May 2010 led to no clear recovery signals until the end of 2011. Notice that the others sector's stock returns seemed more volatile than the three named sectors, though the returns of the various sectors mimic the overall market trend, just with more volatility.

[Insert Figure 1 Here]

Table 1 contains the summary statistics by sector. In terms of size, we find no clear differences across sectors. Leverage is highest for the broker-dealers sector (12.26), followed by insurance (11.93) and others (11.22); the least leveraged sector by far was depositories (7.94). The best return/risk ratio accrues to the brokers-dealers (0.54), followed by insurance companies (0.35), depositories (0.34), and then others (0.32). We classify risk measures using the subindex "ben" to refer to benchmark-based measures (i.e., accounting for common factors only). Measures without this subindex reflect the full model (common factor plus tail dependence effects). Because the *DD* (DD_{ben}) indicates the distance to default over the next six months, lower value implies higher systemic risk for a sector. In the broker-dealers sector, this measure comes closest to default, with an average value of 2.59 (6.01), followed by others at 3.45 (5.51), depositories with 6.31 (8.0), and finally insurance companies at 10.99

(12.18). Furthermore, *NoD* (*NoD*$_{ben}$), or the number of defaults among the 10 biggest financial institutions, achieves the highest values in the others sector at 2.38 (1.42), followed by broker-dealers with 2.26 (0.96). Both depositories with 0.79 (0.26) and insurance companies with 0.36 (0.23) exhibit fewer defaults. Finally, for *PIR* (*PIR*$_{ben}$), the ratio of a sector's price of insurance against financial distress to the sector's total assets, others sector reveals the largest value of 39.90 (15.07), followed by broker-dealers with 22.22 (2.61); depositories and insurance companies again indicated lower values, of 4.50 (0.34) and 3.75 (1.42), respectively. These measures accordingly indicate that the riskiest sectors are broker-dealers and others, followed by depositories and insurance companies. In all cases, the measure from the full model indicates more systemic risk than a measure based on the benchmark.

[Insert Table 1 Here]

Regarding the correlations across measures, *DD* reveals negative correlation with *NoD* (–0.69) and *PIR* (–0.42), whereas *NoD* and *PIR* indicate a positive correlation (0.75). We estimate correlations across the four sectors for each measure too and find that they vary. For example, the highest correlation arises between depositories and broker-dealers for *DD* and *PIR*, as well as between depositories and insurance companies for *NoD*. Correlations across sectors for *PIR* generally are greater than those for the other two measures. The correlations range from 0.44 to 0.82 for *DD*, from 0.41 to 0.87 for *NoD*, and from 0.74 to 0.88 for *PIR*.[29]

2.5. Empirical Analysis

With our empirical analysis, we explore the effect of combining two factors (common factor and tail dependence effects) to measure systemic risk. Therefore, we first document estimation results from the correlated jumps and structural-form models. In the next section, we present a preliminary comparison between the full model and benchmark-based measures,

[29] Detailed information about the correlations for each measure within the four sectors is not reported here but is available on request.

then test whether our full model systemic risk measures constitute leading indicators of benchmark-based ones and of the St. Louis Fed Financial Stress Index (STLFSI).

2.5.1. Estimation Results

2.5.1.1. Tail Dependence Parameters

To characterize the sector-level behavior of the tail dependence effects, which we proxy for with correlated jumps, we average the firm-specific estimates into one single measure for the mean and the volatility of the size of the correlated jumps by sector, denoted *mu_coj* and *std_coj*. With a rolling window approach, we compute the time series for λ, *mu_coj*, and *std_coj*.[30] These estimates describe the properties of simultaneous shocks in the equity market. Figure 2 reports three time-varying variables from 1996 to 2011, by sector.[31]

For λ, depositories and insurance companies indicated similar, smooth moving behaviors: usually below 0.1 before 2006, increasing during 2007, peaking (around 0.3) and staying high for a while, dropping to a pre-crisis level in mid-2009, and increasing again in mid-2011. For broker-dealers, the parameter moved steadily, with low levels before 2005, slight increases in the following two years, and a peak (0.2) near the time of Lehman's failure. After that event, it dropped to a pre-Lehman level, though it appeared more unstable than it is before 2005. Finally, the λ of the others sector fluctuated more frequently before 2006, then reached its peak in the fourth quarter of 2008 (>0.35) and remained at a relatively high level (>0.15) for a longer time during 2008–2009 than the three named sectors. Again we observe a clear increase after mid-2011. Overall then, the intensity of correlated jumps across sectors began to increase before the subprime loan crisis of 2007, reached its peak around the time Lehman

[30] For example, in the case of the parameter λ , we estimate it for a group of the ten largest financial institutions in each sector, using data from January 1996 to December 1996, and assign the calculated value to December 1996. Then we repeat the procedure using data from February 1996 to January 1997 and assign this calculated value of λ to January 1997, and so on.

[31] Specific information about the main systemic events from 2007 to 2011 is available at http://timeline.stlouisfed.org/.

failed, decreased, and then increased again in mid-2011, coincident with the Eurozone crisis. This evidence suggests that the probability of simultaneous jumps is higher during crises.

The average jump size *mu_coj* is close to zero throughout the sample period for insurance companies; it was not in the other three sectors. We identified negative jumps around the time of Lehman's bankruptcy for broker-dealers, others, and depositories, with average sizes of –0.10, –0.07 and –0.05, respectively. The others sector also suffered negative jumps in the first half of 2009, possibly due to events related to the crisis and subsequent bailout of Fannie Mae and Freddie Mac; this sector contains many firms involved in mortgage markets.[32]

For the jump volatility *std_coj*, the behavior appeared similar across sectors: constantly below 0.05 and very stable until the end of 2007, increasing at the beginning of 2008, reaching historically high levels around mid-2009, and dropping to lower levels thereafter.

This collected evidence matches our intuition regarding the model parameters. In most cases, λ and *std_coj* are higher and *mu_coj* displays negative values during episodes of systemic risk. That is, acute stress situations in the financial industry are coincident with higher frequencies of simultaneous, negative, extreme jumps in the stock returns of firms in that industry.

[Insert Figure 2 Here]

To examine whether the correlated jumps display specific behavior during the 2007–2009 crisis, we analyze results for 2005–2011 and compare the estimates across three periods: pre-crisis (July 2005–June 2007), crisis (July 2007–June 2009), and post-crisis (July 2009–

[32] On March 11, 2009, Freddie Mac announced net losses of $23.9 billion for the fourth quarter of 2008 and $50.1 billion for 2008 as a whole. Its conservator submitted a request to the U.S. Treasury Department for an additional $30.8 billion in funding, under a Senior Preferred Stock Purchase Agreement.

June 2011). The results in Table 2 are specific to depositories, broker-dealers, insurance companies, and others (Panels A–D, respectively) and indicate significant differences between the pre-crisis and crisis periods for each group. As expected, the intensity and volatility of correlated jumps are higher in the crisis period; and the mean of correlated jumps is strongly negative in this period.

[Insert Table 2 Here]

The others sector always reveals the highest λ. In the crisis period, it also has the highest value for *std_coj* (0.13) and the lowest *mu_coj* (–0.02), followed by broker-dealers (–0.01). Thus, in this others sector, negative shocks are deeper and more frequent, and their size is more volatile. We also note significant increases in λ during the crisis period. For example, for depositories it increased more than threefold compared with the pre-crisis period (0.13 versus 0.04), doubled in size (0.06 versus 0.03) for broker-dealers, and increased notably (0.19 versus 0.10) in the others sector. The statistical tests thus support our intuition that there was a higher probability of simultaneous negative shocks in the equity market during the 2007–2009 financial crisis, compared with both preceding and posterior periods.

2.5.1.2. Common Factor Parameters

The parameters of the common factor component (benchmark model) are μ, δ, and ξ, which capture the long-run mean of asset returns, exposure to the common factor, and variance in idiosyncratic factors, respectively. We average firm-level estimates to obtain sector-level variables, and to distinguish the estimates of the full model from those of the benchmark model, we use notations of $\mu_{\_ben}$, $\delta_{\_ben}$, and $\xi_{\_ben}$, for the latter. Table 3 contains the estimates by sector, along with the results of the mean tests for estimates derived from the full model and from the benchmark. First, we observe that both δ and ξ are significantly lower than $\delta_{\_ben,}$ and $\xi_{\_ben}$ (see Columns 3, 6, and 9 in Table 3). By construction, the term of correlated jumps should capture some contributions of asset returns from the common factor and from the idiosyncratic factor. Therefore, the decrease in the magnitudes of δ and ξ compared with the benchmark model is likely and expected. Second, insurance companies experience the highest exposure to the common factor (0.72), followed by broker-dealers (0.59); others has the lowest exposure (0.35).

[Insert Table 3 Here]

2.5.2. Systemic Risk Measures: Preliminary Analysis

In this section we outline the stylized facts for three alternative systemic risk measures, based on both our model and the benchmark. The time series of the risk measures from 1996 to 2011 by sector appear in Panels A–C of Figure 3.

[Insert Figure 3 Here]

2.5.2.1. DD

Because the *DD* indicates how far a firm's asset value exceeds its default point for a given sector, it contrasts with conventional risk measures, such that a lower value of *DD* implies higher systemic risk for the sector. In Panel A of Figure 3, the tail dependence effects are of material importance if the red line appears below the blue line—as is the case in all sectors. The tail dependence effects reduce the distance to default during and prior to negative economic events, so *DD* is lower than DD_{ben}. For example, in the depositories sector, the tail dependence effects appeared;

(1) From the end of 1997 to mid-1999 (1997 Asian Crisis, 1998 LTCM debacle) with *DD* equal to 5.1 and DD_{ben} equal to 5.9.[33]

(2) From September 2001 to 2003 (9/11 attack, end of dot.com bubble, credit market

[33] We compute average values of *DD* and DD_{ben} and compare them for specific periods; for example, the average values from the end of 1997 to mid-1999 were 5.1 and 5.9, respectively.

deterioration in 2002[34]) (*DD* 6.5, DD_{ben} 9.9).

(3) From June 2006 (one year prior to the 2007 subprime loan crisis) to mid-2010 (2007–2010 financial crisis), with *DD* (4.5) versus DD_{ben} (7.3).

(4) In the second half of 2011 (European debt crisis), with *DD* (2.4) and DD_{ben} (3.6).

In the insurance sector, the effect arose in 2005–2009 (2005 automotive-downgrade credit crisis, 2007–2010 financial crisis), where *DD* was 10.7 and DD_{ben} equaled 13.2. For others, the effect occurred at three moments: (1) from mid-1998 to mid-1999 (LTCM debacle) (*DD* 3.9, DD_{ben} 5.5); (2) from September 2001 to September 2008 (9/11, end of dot.com bubble, credit market deterioration in 2002, low interest rates and high leverage among financial institutions during 2002–2004, 2007–2008 financial crisis) (*DD* 3.6, DD_{ben} 7.1); and (3) during the second half of 2011 (European debt crisis) (*DD* 1.7, DD_{ben} 3.8). In 2008–2009, the measures from both the full and benchmark models signaled that the others sector was very close to default.

2.5.2.2. NoD

Regarding the number of simultaneous defaults among the ten biggest financial institutions for each sector (Panel B, Figure 3), the tail dependence effect is significant for managers when the red line is above the blue line, that is, when *NoD* is larger than NoD_{ben}, which is mostly the case in our findings. That is, tail dependence effect increased significantly during the 2007–2010 financial crises across all four sectors. Before 2007, this effect was less noticeable than the *DD* measures were. For example, for depositories, we find this effect only in 1998 (*NoD* 0.35, NoD_{ben} 0.04) and 2002 (*NoD* 0.29, NoD_{ben} 0.02); for broker-dealers, it arose only between 1996 and 2003 (*NoD* 2.71, NoD_{ben} 0.86). During the 2007-2010 crisis, *NoD* peaked, and the others sector emerged as the most risky, such that 9 of the 10 largest

[34] Huang *et al.* (2009) document that systemic risk exhibits substantial increases during 2002, due to the credit market deterioration.

firms were expected to default. Depositories (8 of 10) and insurance companies (5 of 10) also exhibited substantial risk of default. Thus, risks in the financial industry increases through the channel of tail dependence in equity markets, especially in tough times.

2.5.2.3. PIR

Panel C of Figure 3 contains the time variation of *PIR*, or the ratio of the sector's price of insurance against financial distress to its aggregate asset value. The tail dependence effects are materially important for virtually all sectors, and the measure display especially strong effects of tail dependence during the financial crisis. Among broker-dealers for example, the *NoD* measure suggests similar levels of systemic risk for both the LTCM debacle and Lehman's bankruptcy (6 of 10 defaulting firms), but *PIR* signals greater systemic risk for the latter event (200) than the former (50). Empirical evidence also suggests that including tail dependence improves the model's ability to anticipate stressful periods. For example, in the others sector, *PIR* increased noticeably by October 2007, when Fannie Mae and Freddie Mac signaled their troubles due to the subprime crisis. In the broker-dealers and depositories sectors, *PIR* increased by March 2008, around the time of Bear Sterns's failure. However PIR_{ben} did not show a clear upward trend until September 2008.

2.5.3. Predictability

A key criterion of the quality of a systemic risk indicator is its forecasting power. Therefore, we examine the lead-lag relationship between the full model–based measures and the benchmark-based ones. We use Granger causality whether our measures could forecast an index of financial distress. In particular, we used the St. Louis Fed Financial Stress Index (STLFSI), as proposed by Kliesen and Smith (2010).[35] This index is publicly available and

[35] The STLFSI is constructed by using 18 data series for different financial variables, including interest rates (effective federal funds rate, 2-year Treasury, 10-year Treasury, 30-year Treasury, Baa-rated corporate, Merrill Lynch High-Yield Corporate Master II Index, and Merrill Lynch Asset-Backed Master BBB-rated), yield spreads (yield curve: 10-year Treasury minus 3-month Treasury, corporate

based on a principal component analysis of a broad range of financial prices and rates from different financial markets. Figure 4 shows the monthly time series of STLFSI from December 1996 to December 2011.[36] We find a local peak near the 1998 LTCM debacle, smooth increases between 2001 and 2002, increases after September 2007 (subprime crisis), a maximum level in September 2008 (Lehman bankruptcy), and two local peaks in mid-2010 and mid-2011 (acute stress periods in the Eurozone debt crisis).

[Insert Figure 4 Here]

2.5.3.1. Granger Causality Test

Because unit roots test offer conflicting results,[37] we rely on Granger causality (GC) tests in Table 4 for both levels (Panel A) and first differences (Panel B). For these tests, we use optimally chosen lags, corrected after controlling for heteroskedastic and correlated errors.[38]

Regarding the GC results for series in levels between the full model and benchmark measures, the full model measures lead (usually by one or two months) benchmark-based ones in 10 of 12 cases; the remaining 2 cases exhibit bidirectional causality. That is, including the correlated jump factor improves the model's forecasting power in most cases over the benchmark.

The GC results for the comparison of the full model with the STLFSI in turn show that in 4 of 12 cases, the full model measures lead the STLFSI; in 2 cases, the STLFSI lead the

---

Baa-rated bond minus 10-year Treasury, Merrill Lynch High-Yield Corporate Master II Index minus 10-year Treasury, 3-month London Interbank Offering Rate–Overnight Index Swap [LIBOR-OIS] spread, 3-month Treasury-Eurodollar [TED] spread, and 3-month commercial paper minus 3-month Treasury bill.), and other indicators (J.P. Morgan Emerging Markets Bond Index Plus, Chicago Board Options Exchange Market Volatility Index [VIX], Merrill Lynch Bond Market Volatility Index [1-month], 10-year nominal Treasury yield minus 10-year Treasury Inflation Protected Security yield, and Vanguard Financials Exchange-Traded Fund). Furthermore, the index is built by using principal component analysis to extract the factors responsible for the co-movement of a group of variables.

[36] We use monthly STLFSI, though the highest frequency is weekly, to match our data intervals.

[37] We also employed several unit root tests, including Augmented Dickey-Fuller, GLS Dickey-Fuller, and Perron (1997) with structural breaks in the mean, for the trends and both elements simultaneously. The detailed results are available on request.

[38] The optimal number of lags was chosen on the basis of Schwarz's Bayesian information criterion.

full model; and 3 cases indicate bidirectional causality. Two broker-dealer sector measures (*DD*, *NoD*) and all the insurance sector systemic risk measures lead the STLFSI, by an average period of one month. Therefore, the measures in these two sectors are the most informative leading indicators. If *DD* and *NoD* measures increase in both sectors in a given month, a subsequent increase in the STLFSI index seems very likely indeed.

Using first difference data series (Panel B, Table 4), the full model–based measures lead (usually by one or two months) the benchmark-based ones in 8 of 12 cases; the reverse is true in 2 cases. These results generally agree with those we gathered from the series in levels. In the comparison of the full model measures and the STLFSI index, we find that the full model lead the STLFI in five cases, whereas the reverse occurs in 2 cases. That is, in agreement with series in levels, two broker-dealer systemic risk measures (*DD*, *NoD*) lead the STLFSI, as does one measure from the insurance sector (*PIR*).

[Insert Table 4 Here]

Thus, the measures based on the full model contain more updated information than benchmark-based ones. Two measures related to broker-dealers (*DD* and *NoD*) and one measure in the insurance sector (*PIR*) provide leading information about the STLFSI index across all cases.[39]

[39] In addition to testing forecasting power over the whole sample period, we explore the full model measures could identify early warning signs of the 2007–2010 financial crisis better than the benchmark-based measures. We apply the Quandt-Andrews breakpoint test to date structural changes or break dates, identified by testing for structural changes in the coefficient of the autoregressive model with an order of 1 for the persistence test and of the constant term in the regressions for the level test. The changes should be primarily manifest in the leading indicators, then later in other variables. For the persistence test, the break dates identified by the full model measures across sectors all occur before July 2007 (the conventional crisis's starting point), and always lead the benchmark. The earliest two turning points happen for depositories and broker-dealers, in February 2006 and March 2006, respectively—that is, more than a year before July 2007. The full model measures also lead (coincide with) benchmark-based measures in 9 (1) of 12 cases. For the level test, the full model measures lead (coincide with) benchmark ones in 8 (2) cases. Overall the evidence supports the notion that considering tail dependence effects besides a common factor does provide more timely warning signals.

2.5.3.2. Predictive Power

To further compare the predictive ability of both models (benchmark and FM) in predicting STLFSI, we first run a predictive regression, including as explanatory variables the lagged terms of STLFSI and of the benchmark (pure common component model):

$$STLFSI_t = c + \sum_{s_1=1}^{k_1} \alpha_{s_1} STLFSI_{t-s_1} + \sum_{s_2=1}^{k_2} \beta_{s_2} Benchmark_{t-s_2} + \varepsilon_t . \quad (25)$$

Next we include the lagged terms of the FM factor (common plus extreme movement model) to determine the incremental predictive ability it may provide, using the following regression:

$$STLFSI_t = c + \sum_{s_1=1}^{k_1} \alpha_{s_1} STLFSI_{t-s_1} + \sum_{s_2=1}^{k_2} \beta_{s_2} Benchmark_{t-s_2} + \sum_{s_3=1}^{k_3} \omega_{s_3} FM_{t-s3} + \varepsilon_t . \quad (26)$$

where k_1, k_2, and k_3 are optimal lags selected according to the Bayesian information criterion.

We use an *F-test* to determine if the difference in forecasting ability, as measured by R^2 values on the restricted model of Equation (25) and the unrestricted model of Equation (26), differs significantly from zero. Formally, the *F-statistic* is computed as

$$F\text{-}statistic = [(R^2_{\_eq.(2)} - R^2_{\_eq.(1)}) / (k_1+k_2+k_3 - (k_1+k_2))] / [(1- R^2_{\_eq.(2)}) / (N - (k_1+k_2+k_3) - 1)], \quad (27)$$

where N is the sample size, and the degrees of freedom are computed as $v_1= (k_1+k_2+k_3 - (k_1+k_2))$ and $v_2= (N - (k_1+k_2+k_3) - 1)$. Table 5 reports results and reveals cases where R^2 is higher in Equation (26) than in Equation (25), using bold font.

For the data series in levels (Panel A of Table 5), in 8 of 12 cases the FM models offer additional explanatory power, as indicated by the higher R^2 for Equation (26) than Equation

(25). This additional explanatory power is particularly significant in five cases: *DD* on depositories, *DD* on insurance companies, *NoD* on others, *PIR* on broker-dealers, and *PIR* on insurance companies. For data series in first differences (Panel B of Table 5), in 10 of 12 cases, FM models have some additional explanatory power, especially notable in five cases: *DD* on insurance companies, *NoD* on depositories, *NoD* and *PIR* on broker-dealers, and *PIR* on insurance companies. The evidence thus suggests that FM-based measures have extra predictive power in comparison with the benchmark model, especially in the case of *DD* on insurance companies and *PIR* on broker-dealers and insurance companies.

[Insert Table 5 Here]

2.6. Conclusion

Growing evidence suggests that systemic risk results from at least two driving forces: the common factor exposure to market-wide shocks and the tail dependence effects that arise from links among extreme stock returns. Modeling the relative importance of these two factors is critical; we seek to contribute to this literature stream by proposing a new structural-form model that includes both factors. For our framework, the common factor component is based on correlations of a financial institution's individual stock returns with an aggregate common factor, and we proxy for tail dependence effects with a correlated jumps factor. The empirical implications of our model tests are consistent with extant evidence; in particular, they suggest that simultaneous extreme negative movements across large financial institutions are stronger in bear markets than in bull markets.

With an empirical application based on stock market data for four sectors of the U.S. financial industry during 1996–2011, we demonstrate that ignoring the effect of tail dependence will lead to underestimates of the level of systemic risk. By accounting for tail dependence effects, we gain extra forecasting power, compared with a benchmark model. Not all sectors provide equally valuable systemic risk indicators though. Rather, two measures (*DD*, *NoD*) in the broker-dealer sector and one measure (*PIR*) from the insurance sector systematically lead the St. Louis Fed Financial Stress Index (STLFSI).

Looking forward, a comparison of our measures with other measures based on alternative asset markets would offer an interesting topic for further investigation. The application of our measures for asset pricing, hedging strategies, portfolio diversification, and risk management purposes represent other natural directions for further research.

Appendices

Appendix A

We apply the theorem of the law of total variance,

$$Var\left(Y\right)=E_X\left[Var\left(Y\mid X\right)\right]+Var_X\left[E\left(Y\mid X\right)\right]. \text{ (A.1)}$$

In our case, we have,

$$Y\equiv Q_j N\left(\Delta t\right)=\sum_{k=1}^{N(\Delta t)} Q_j^{(k)}\left(\Delta t\right), \text{ and } X=N\left(\Delta t\right). \text{ (A.2)}$$

Therefore,

$$\begin{aligned} Var^P\left(Q_j N\left(\Delta t\right)\right) &= E_N\left[b_j^2 N\left(\Delta t\right)\right]+Var_N\left[N\left(\Delta t\right)a_j\right] \\ &= b_j^2\lambda + a_j^2\lambda \\ &= \left[a_j^2+b_j^2\right]\lambda \end{aligned} \text{ . (A.3)}$$

Finally, we assume that all random variables appear in the asset–log return process described by Equation (1) are independent and derive the variance of asset returns as follows:

$$Var\left(v_{j,t}\mid \varphi_{t-1}\right)\equiv\sigma_{j,t}^2=\delta_j^2 h_t+\xi_j+\lambda\hat{b}_j^2, \text{ (A.4)}$$

where $\hat{b}_j^2=a_j^2+b_j^2$.

Appendix B

Because Q_k are normally i.i.d. random variables, distributed independently of $N(T)$, by iterated expectations, we know

$$
\begin{aligned}
E\left[e^{\phi Q_j N(T)}\right] &= E\left[e^{\phi \sum_{k=1}^{N(T)} Q_{j,k}}\right] = E\left[\prod_{k=1}^{N(T)} e^{\phi Q_{j,k}}\right] = E_N\left[E_{Q_j|N}\left[\prod_{k=1}^{N(T)} e^{\phi Q_{j,k}} \mid N(T)\right]\right] \\
&= \sum_{i=0}^{\infty} p_i(\lambda T) E\left[\prod_{k=1}^{i} e^{\phi Q_{j,k}}\right] = \sum_{i=0}^{\infty} p_i(\lambda T) \prod_{k=1}^{i} E\left[e^{\phi Q_{j,k}}\right] \\
&= \sum_{i=0}^{\infty} \frac{e^{-\lambda T}(\lambda T)^i}{i!}\left(e^{\left(a_j\phi+\frac{1}{2}b_j^2\phi^2\right)}\right)^i = e^{-\lambda T}\sum_{i=0}^{\infty}\frac{1}{i!}\left(\lambda T e^{\left(a_j\phi+\frac{1}{2}b_j^2\phi^2\right)}\right)^i \\
&= e^{-\lambda T} e^{\lambda T \exp\left(a_j\phi+\frac{1}{2}b_j^2\phi^2\right)} = e^{\lambda T\left(\exp\left(a_j\phi+\frac{1}{2}b_j^2\phi^2\right)-1\right)}
\end{aligned}
\quad . \text{(B.1)}
$$

Appendix C

Type	Company Name	Start Date	End Date	Number of Observations	Size (millions)	LVG
Depositories	'BANK OF AMERICA CORP'	199601	201112	181	13.556	9.194
Depositories	'BANK OF NEW YORK MELLON CORP'	200310	201112	55	12.037	5.709
Depositories	'BANK ONE CORP'	199601	200406	91	12.101	5.949
Depositories	'BANKAMERICA CORP-OLD'	199601	199809	22	12.391	7.568
Depositories	'BANKERS TRUST CORP'	199601	199905	30	11.693	16.393
Depositories	'BB&T CORP'	200401	201112	72	11.745	7.345
Depositories	'CITICORP'	199601	199809	22	12.510	6.568
Depositories	'FIFTH THIRD BANCORP'	200308	200708	20	11.473	4.391
Depositories	'FIRST CHICAGO NBD CORP'	199601	199809	22	11.639	7.736
Depositories	'FLEETBOSTON FINANCIAL CORP'	199604	200403	69	11.846	5.777
Depositories	'GOLDEN WEST FINANCIAL CORP'	200501	200609	10	11.585	6.224
Depositories	'JPMORGAN CHASE & CO'	199601	201112	181	13.565	10.194
Depositories	'KEYCORP'	199712	200408	27	11.294	7.799
Depositories	'MORGAN (J P) & CO'	199601	200012	49	12.383	12.952
Depositories	'NATIONAL CITY CORP'	199807	200812	109	11.614	6.439
Depositories	'PNC FINANCIAL SVCS GROUP INC'	199711	201112	47	12.049	8.966
Depositories	'REGIONS FINANCIAL CORP'	200704	201112	46	11.856	17.872
Depositories	'STATE STREET CORP'	200305	201112	50	11.875	8.214
Depositories	'SUNTRUST BANKS INC'	199904	201112	142	11.829	9.124
Depositories	'U S BANCORP'	200107	201112	115	12.260	5.103
Depositories	'U S BANCORP/DE-OLD'	200010	200205	9	11.369	4.466
Depositories	'WACHOVIA CORP'	199601	200812	145	12.586	6.926

Depositories	'WASHINGTON MUTUAL INC'	199801	200808	117	12.334	8.449
Depositories	'WELLS FARGO & CO -OLD'	199610	199810	14	11.572	4.678
Depositories	'WELLS FARGO & CO'	199601	201112	165	12.771	5.456
Broker-Dealers	'AMERIPRISE FINANCIAL INC'	200604	201112	58	11.560	11.357
Broker-Dealers	'AXA FINANCIAL INC'	199601	200012	49	11.872	18.052
Broker-Dealers	'BEAR STEARNS COMPANIES INC'	199601	200805	138	12.091	27.973
Broker-Dealers	'BLACKROCK INC'	200701	201112	49	10.378	3.734
Broker-Dealers	'CITIGROUP GLOBAL MKTS HLDGS'	199601	199710	11	12.095	41.126
Broker-Dealers	'CREDIT SUISSE USA INC'	199604	200010	44	11.085	18.551
Broker-Dealers	'DAIN RAUSCHER CORP'	199601	199702	3	7.725	8.450
Broker-Dealers	'E TRADE FINANCIAL CORP'	200002	201112	132	10.338	14.236
Broker-Dealers	'EDWARDS (A G) INC'	199601	200207	49	8.304	1.880
Broker-Dealers	'FRANKLIN RESOURCES INC'	199601	200702	56	8.805	1.194
Broker-Dealers	'GOLDMAN SACHS GROUP INC'	199909	201112	137	13.195	11.249
Broker-Dealers	'INTERACTIVE BROKERS GROUP'	200710	201112	40	10.300	36.641
Broker-Dealers	'JEFFERIES GROUP INC'	200107	201112	97	9.717	7.315
Broker-Dealers	'LEGG MASON INC'	200104	200311	19	8.614	2.492
Broker-Dealers	'LEHMAN BROTHERS HOLDINGS INC'	199601	200808	141	12.393	22.165
Broker-Dealers	'MERRILL LYNCH & CO INC'	199601	200812	145	12.947	12.367
Broker-Dealers	'MORGAN STANLEY'	199601	201112	181	13.173	14.750
Broker-Dealers	'PAINE WEBBER GROUP'	199601	200010	47	10.921	16.013
Broker-Dealers	'QUICK & REILLY GROUP INC'	199603	199801	12	8.117	5.102
Broker-Dealers	'RAYMOND JAMES FINANCIAL CORP'	199703	201112	102	8.975	5.428
Broker-Dealers	'SCHWAB (CHARLES) CORP'	199604	201112	178	10.452	3.052
Broker-Dealers	'SWS GROUP INC'	199707	200202	15	8.316	14.279
Broker-Dealers	'TD AMERITRADE HOLDING CORP'	200301	201112	94	9.667	2.903
Broker-Dealers	'TD WATERHOUSE GROUP INC'	199911	200110	13	9.238	2.259
Insurance Companies	'AETNA INC'	199601	200011	48	11.476	9.204
Insurance Companies	'AFLAC INC'	200904	201112	22	11.314	4.714
Insurance Companies	'ALLSTATE CORP'	199607	201112	175	11.666	5.097
Insurance Companies	'AMERICAN GENERAL CORP'	199601	200107	56	11.336	7.109
Insurance Companies	'AMERICAN INTERNATIONAL GROUP'	199601	201112	181	13.028	36.671
Insurance Companies	'CIGNA CORP'	199601	200508	105	11.479	9.051
Insurance Companies	'CNA FINANCIAL CORP'	199601	200302	63	11.049	9.223
Insurance Companies	'CNO FINANCIAL GROUP INC'	200001	200108	7	10.826	15.516
Insurance Companies	'GENERAL RE CORP'	199601	199705	6	10.476	3.369
Insurance Companies	'GENWORTH FINANCIAL INC'	200410	201112	76	11.587	23.942
Insurance Companies	'HANCOCK JOHN FINL SVCS INC'	200007	200403	34	11.399	9.408
Insurance Companies	'HARTFORD FINANCIAL SERVICES'	199604	201112	178	12.231	19.248
Insurance Companies	'HARTFORD LIFE INC -CL A'	199710	200005	21	11.566	83.438

Insurance Companies	'LINCOLN NATIONAL CORP'	199601	201112	181	11.627	15.279
Insurance Companies	'LOEWS CORP'	199601	201002	106	11.185	7.264
Insurance Companies	'METLIFE INC'	200010	201112	124	12.878	13.855
Insurance Companies	'NATIONWIDE FINL SVCS -CL A'	199807	200812	115	11.490	68.231
Insurance Companies	'PRINCIPAL FINANCIAL GRP INC'	200204	201112	106	11.706	13.231
Insurance Companies	'PROVIDIAN CORP'	199601	199702	3	10.179	6.585
Insurance Companies	'PRUDENTIAL FINANCIAL INC'	200204	201112	106	12.903	17.108
Insurance Companies	'TRANSAMERICA CORP'	199601	199805	12	10.782	9.311
Insurance Companies	'TRAVELERS COS INC'	199610	201112	85	11.542	5.642
others	'AMERICAN EXPRESS CO'	199601	201112	181	11.817	3.668
others	'ANNALY CAPITAL MANAGEMENT'	200207	201112	55	10.721	7.537
others	'APARTMENT INVST & MGMT CO'	200204	200308	6	9.102	2.843
others	'ASSOCIATES FIRST CAP -CL A'	199610	200011	39	10.991	6.809
others	'BENEFICIAL CORP'	199601	199806	19	9.670	5.548
others	'CAPITAL ONE FINANCIAL CORP'	200007	201112	127	11.083	5.916
others	'CAPSTEAD MORTGAGE CORP'	199601	200205	40	9.256	18.884
others	'CIT GROUP INC'	200301	201112	81	10.998	10.818
others	'CIT GROUP INC-OLD'	199804	200105	27	10.143	11.133
others	'CITIGROUP INC'	199601	201112	181	13.683	13.404
others	'CME GROUP INC'	200901	201112	25	10.546	1.644
others	'COUNTRYWIDE FINANCIAL CORP'	199601	200806	139	10.463	5.476
others	'DEAN WITTER DISCOVER & CO'	199601	199705	6	10.476	4.333
others	'DISCOVER FINANCIAL SVCS INC'	200712	201112	38	10.677	6.766
others	'FANNIE MAE'	199601	201006	163	13.400	84.908
others	'FEDERAL HOME LOAN MORTG CORP'	199604	201006	160	13.097	125.524
others	'FINOVA GROUP INC'	199601	200201	44	9.147	23.722
others	'FIRST USA INC'	199601	199705	6	8.864	3.004
others	'GENERAL GROWTH PPTYS INC'	200504	201111	11	10.223	5.368
others	'HELLER FINANCIAL INC'	199810	200109	25	9.679	15.190
others	'HOST HOTELS & RESORTS INC'	200107	200305	12	9.025	3.650
others	'HSBC FINANCE CORP'	199601	200302	75	10.739	3.684
others	'IMPAC MORTGAGE HOLDINGS INC'	200603	200705	4	10.231	37.595
others	'INTERCONTINENTALEXCHANGE INC'	201101	201112	1	10.248	3.902
others	'MF GLOBAL HOLDINGS LTD'	200801	201109	34	10.828	65.259
others	'NELNET INC'	200708	201112	17	10.246	43.709
others	'NEW CENTURY FINANCIAL CORP'	200601	200701	2	10.278	13.369
others	'SIMON PROPERTY GROUP INC'	199901	201102	58	9.564	3.249
others	'SLM CORP'	200210	201112	100	11.578	16.639
others	'STUDENT LOAN CORP'	199607	201012	83	9.841	11.464
others	'THORNBURG MORTGAGE INC'	200310	200811	51	10.414	15.003

CHAPTER 3

Financial Crises, Financing Sources, and Default Risks

3.1. Introduction

As the 2007−2009 episodes clearly illustrate, banking and financial markets crises negatively impact real economy corporate sectors, leading to lower stock market valuations, lower investments, reductions in hiring, and a subsequent decrease in aggregate economic activity (see Chava and Purnanandam (2011), Duchin Ozbas, and Sensoy (2010), Lemmon and Roberts (2010), among others). However, there is not an agreement about the mechanism through which these crises (originated in the financial sector) impact the default risk of real-economy firms.[40]

Extant literature provides three alternative views on this mechanism. The first one is the Bank Supply Shock Theory (BSST henceforth). It states that, as a response to shocks in the financial system, banks do not renew loans, increase borrowing costs and refrain from issuing new loans (Ivashina and Scharfstein (2010)), and consequently the impaired bank financing channel generates stronger adverse impacts (e.g. decreases in asset value, increases in asset volatility) on bank-dependent firms (Chava and Purnanandam (2011)). Empirical evidence does suggest that many bank-dependent firms present higher default probabilities in times of credit crunch; Khwaja and Mian (2008), Paravisini (2008), and Schnabl (2012) document this effect in emerging markets. However in the case of developed economies the evidence is not particularly conclusive.[41] The second view is the Credit Supply Shock Theory (CSST henceforth) which asserts that credit-dependent (not just bank-dependent) firms should face

[40] Beyond firm-level risk characteristics, theoretical and empirical studies both indicate that macroeconomic shocks increase firms' default probabilities (e.g., Bonfim (2009), Chen (2010), Jacobson, Lind´e, and Roszbach (2013)). Abundant evidence suggests that financial crises are likely sources of macroeconomic shocks.

[41] Some argue that this channel has strong real effects (Bernanke (1983), Peek and Rosengren (2000)), but others find the economic impact to be insignificant (Ashcraft (2006)).

trouble because the crisis affects all credit channels (Gorton (2010)). In this vein, recent theoretical models of He and Xiong (2012b) and Chen et al. (2013) imply that default risks should increase due to debt market frictions when firms rollover their debts.[42] A third explanation is the Demand Shock Theory (DST henceforth) which suggests that firms react to decreases in the demand for firms' products by cutting borrowing and investments, leading to the reduction on growth and profitability in a similar way, irrespective of their financing structures (Kahle and Stulz (2013)).

However, the question of to what extent the source of debt financing (bank loans and/or public debts) affects default risks could be considered as an empirical question, since all channels of debt financing are likely to be affected during a crisis (Adrian, Colla, and Shin (2012)).[43] In this paper we address this question using an extensive database and, as far as we know, this is the first study providing direct empirical evidence on this issue.

Furthermore, we examine whether bank-dependent firms can substitute bank loans by issuing publicly traded debts, to mitigate the increase of default risks due to bank lending supply shocks. We name this notion as the "substitution effect".[44] We posit that, if the substitution effect applies, the increase of default risks is expected to be lower for bank-dependent firms having ready access to public debt markets than for otherwise similar firms lacking this access. Adrian et al. (2012) show that credit spreads significantly increased in both new issuances of banks loans and corporate bonds during the 2007−2010 crises. Since

[42] Their models assume that debt market illiquidity arises in corporate bond markets, and thus firms that mainly rely on financing from public debt markets are expected to experience larger increases in default risks. This implication can also be applied to the case of bank lending shocks, since debt financing costs also increase in bank loan markets during financial crises, which is consistent with the setting of models capturing debt market frictions. Thus, we may also observe greater credit risks for firms that rely on bank loans, and thus more generally, we should expect increases in default risk to all credit-dependent firms.

[43] Adrian et al. (2012) find that during the 2007−2010 financial crises credit spreads significantly increased in both new issuance of banks loans and corporate bonds in the U.S. market, implying that the firms' main financing sources (bank lending and corporate debt markets) were more expensive.

[44] Previous empirical results on testing the substitution effect are mixed (see Bernanke (2007), Chava and Purnanandam (2011)), Lemmon and Roberts (2010), Carvalho et al. (2012)).

higher credit spreads imply higher default risks, this may be considered indirect evidence against the substitution effect. In this paper, we directly test the substitution effect on default risks.

We develop a novel empirical methodology to address the question at hand. First, we propose a new identification strategy by looking at firms' ex-ante reliance of various financing sources. A firm is classified as credit-dependent when there are records of its bank borrowing over the past five years prior the onset of financial crises, or there is evidence of the firm's access to public debt markets. Otherwise we classify it as non-credit-dependent firm. Once defined the set of credit-dependent firms, we further divide this group into five categories based on their dependence of bank loans, public debts, or both.[45] We use difference-in-differences estimations by examining cross-sectional heterogeneity of time-series changes in Distance-to-Default (DD) across firms.[46] Our methodology also controls for many relevant firm risk characteristics: size, leverage, volatility, equity return, ratio of cash to assets, ratio of net income to assets, and industry effect.[47]

The empirical application is based on an appropriate selection from all listed non-financial firms in the U.S. market during the period of 2006Q3−2010Q1 totalizing 113,409 firm-month observations. We analyze the change of DD (relative to DD during the pre-crisis period) over four time stages: first-year crisis (2007Q2− 2008Q2); pre−Lehman (2008Q2); post−Lehman (2008Q3−2009Q1); and last-year crisis (2009Q2−2010Q1). Using the full sample, we find that default risks significantly increased about 50% on average across all

[45] We consider a firm of having strong bank dependence when it borrows two or more than two loans from the same lead bank over the past five years before the end of June 2006. On the other hand, we consider a firm of having weak bank dependence when it has records of bank loans, but not enough to qualify as strong bank-dependent firm. We rely on credit ratings as indicators of public-debt dependence. The detailed information on these issues is in Section 3.

[46] DD is a well-known market-based forward-looking default risk measure based on Merton (1974).

[47] These variables are motivated by the hazard model literature, and are among the most important determinants to default risks (etc., Shumway (2001); Chava and Jarrow (2004); and Campbell, Hilscher, and Szilagyi (2008)).

firms (irrespective of their financing dependence) from the pre-crisis period to the last-year crisis period. However, in the first year of the crisis, this increase varies from a strongly significant 22.8% (in the case of unrated firms strongly dependent on bank financing) to an insignificant 5.2% (in the case of rated firms without banking dependence). Our findings using the matched sample (after accounting for other observed risk characteristics) give a more nuanced picture.[48] We find that, during the first-year crisis period, default risks increase more for firms that rely on banks for financing than for other types of credit-dependent firms and non-credit-dependent firms. This evidence is not inconsistent with the BSST, but it is inconsistent with CSST and DST. Furthermore, our evidence is not consistent with the substitution effect because we find that there is no evidence of economically or statistically important differences across bank-dependent firms, irrespective of their capabilities of accessing public-debt markets.

We contribute to literature on several dimensions. First, we add to the literature on real-economy impacts of financial crises,[49] by providing evidence of the effect of these crises on firm's default risks. In spite of the large volume of existing studies on the 2007−2009 crises, our study is one of few that empirically links shocks in the financial system to corporate default risks.[50] Second, this paper contributes to the literature on the mechanism linking financial shocks and real economic activities.[51] In a nutshell, our results suggest that the

[48] Note that heterogeneity of default risks across firms might be related to other factors (e.g. leverage) besides the impact of financing sources. The matched sample that balances these fundamental differences, gives more reliable results because it excludes other factors that are also related to a firm's default. Also, the first-year period has been viewed in the literature as the one particularly well-suited to distinguish among competing explanations (BSST, CSST, DST). The rationale is that firms' default probabilities are less affected by demand side effect at the early stage of crisis period, whereas in subsequent periods, this distinction is much more difficult to address due the heightened overall uncertainty (e.g., Duchin et al. (2010), Kahle and Stulz (2013)). Thus, evidence based on the matched sample during the first-year crisis (in our case, 2007Q3−2008Q2) should be the more informative.
[49] See Dell'Ariccia, Detragiache, and Rajan (2008), Kahle and Stulz (2013) and others.
[50] Khwaja and Mian (2008), Paravisini (2008), and Schnabl (2012) also study how financial crises affect borrowers' default probabilities. Different from our study, they concentrate on emerging markets, but our paper deals with the U.S. market . Furthermore, they focus only on firms that obtain financing from banks. But our paper is more general because we focus on all firms.
[51] See Duchin et al. (2010), Gorton (2010), Campello, Graham, and Harvey (2010), Chava and Purnanandam (2011), Kahle and Stulz (2013), and Lemmon and Roberts (2010)).

BSST receives more support from the empirical evidence than alternative explanations. Third, we make a contribution to the literature of the substitution effect (e.g., Carvalho et al. (2012), Chava and Purnanandam (2011)), Lemmon and Roberts (2010)) by, for the first time as far as we know, examining whether accessing public-debt market helps bank-dependent firms mitigate their default risks during weak economic times. Our result does not support the substitution effect because we find there is no significant difference of changes in DD for bank-dependent firms, irrespective of their capabilities of accessing public debt markets during the 2007−2010 financial crises.

Fourth, our study adds to the literature establishing the linkage between debt structures and credit risks, where it indicate that rollover risks driven by debt maturity should be viewed as an additional source of credit risks (e.g., Chen et al. (2012), He and Xiong (2012a), He and Xiong (2012b), and Gopalan, Song, and Yerramilli (2013)). Our paper is different from other studies because we pay attention to an element of the debt structure hitherto neglected, namely the source of financing. Our findings suggest that it plays a significant role as a determinant of default risks.

Fifth, extant literature suggests that firms' credit quality influences their financing choices.[52] However, the reverse question, i.e. whether and how financing decisions affect firms' credit risks has not been satisfactorily addressed in our view. Ours is one of few papers providing empirical evidence on this issue by shedding light on the link between financing sources prior to the a financial crisis and the behavior of firms' default risks during the financial crisis.

Information related to borrowers' credit quality is a fundamental determinant of debt contracting and of credit spreads. Our work provides useful information for policy makers

[52] For example, Denis and Mihov (2003) find that firms with the highest credit quality borrow from public sources, firms with average credit quality borrow from banks, and firms with lowest credit quality borrow from non-bank private lenders.

interested in understanding to what extent impairments in the bank lending channel contributes to an increase in the probability of bankruptcies thus deepening recessions. Monetary policy can work through its impact on the bond-market rate of interest or on the supply of intermediated loans. Our key result (firms dependent on bank loans suffer stronger increases in default probabilities than firms dependent on bond markets) suggests that regulators should put high in their agendas timely actuations to fix the banking lending channel when a financial crisis materializes

The remainder of the paper is organized as follows. Section 2 motivates the research question. Section 3 describes the identification strategy and empirical methodology. Section 4 illustrates the data. Section 5 provides empirical results. Section 6 presents some robustness tests. We conclude in Section 7 with a summary of our results.

3.2. Motivation and Literature Review

In this section we motivate the research question and review relevant literature.

3.2.1. Does Distance-to-Default Change during Financial Crises?

To address this point we rely on Merton's (1974) basic framework. We define firm value at time *t* as *V(t)*. By definition, *V(t) = E(t) + D(t)*, where *E(t)* and *D(t)* are equity market value and debt market value at time *t*, respectively. To clarify the analysis, we consider only three time periods *t*, *t+1, t+2*. We define the default barrier as *F(t)* which is the face value of a firm's at time *t* . Given asset return volatility $\sigma_V(t)$, at time t, distance-to-default (*DD(t)*) can be computed at time *t* as

$$DD(t) = \frac{E_t(V(t+1) - F(t))}{\sigma_V(t)E_t(V(t+1))} \tag{1}$$

where $E_t(V(t+1))$ is the expected asset value at time *t+1*, when debt matures, as seen at time *t.* We assume that $E_t(V(t+1)) = V(t)(1+R)$ where *R* is the expected asset growth rate. If

$E_t(V(t+1)) < F(t)$ then we set $DD(t)$=0. To clarify the exposition and without loss of generality[53] we assume $R = 0$ and then equation (1) simplifies to

$$DD(t)\frac{1}{\sigma_V(t)}\times\frac{V(t)-F(t)}{V(t)} \tag{2}$$

Suppose that a financial crisis happens at $t+1$, and a partial impairment in the banking channel materializes. Banks do not give new loans but refinance a proportion k, of the existing debt until period $t+2$ ($0 \leq k \leq 1$), so the firm only has to pay back $(1-k)F(t)$ at $t+1$ and keeps $kF(t)$ in its books until $t+2$. We assume that $V(t+1) > (1-k)F(t)$ (otherwise the firm defaults) then,

$$V(t+1) = V(t) - (1-k)F(t) \tag{3}$$

Distance to default at $t+1$ is defined similarly as:

$$DD(t+1)=\frac{V(t+1)-kF(t)}{\sigma_V(t+1)V(t+1)} \tag{4}$$

Substituting equation (3) into (4) gives

$$DD(t+1)=\frac{1}{\sigma_V(t+1)}\times\frac{V(t)-F(t)}{(V(t)-(1-k)F(t))} \tag{5}$$

The factor multiplying the inverse of the volatility in equation (5) is higher or equal than it in equation (2) and lower or equal than one. Therefore if asset volatility does not change from t to t+1, then we should observe $DD(t) \leq DD(t+1)$. Given that the numerators in equation (2) and (5) are the same, $DD(t+1)$ will be lower than $DD(t)$ if

$$\sigma_V(t+1)>\sigma_V(t)\frac{V(t)}{V(t)-(1-k)F(t)} \tag{6}$$

If there is a full refinancing, this condition simplifies to

[53] The results of this section are essentially the same if we allow for $R\neq 0$.

$$\sigma_V(t+1) > \sigma_V(t) \qquad (7)$$

Or in other words, in order to observe a decrease in distance-to-default in the crisis period (in comparison with the pre-crisis period), asset volatilities in the crisis period should be higher than in pre-crisis period, and the increase being dependent on the degree of refinancing. The higher the refinanced proportion *k* the lower the difference between asset volatilities should be, in order to ensure that *DD(t+1)* is lower than *DD(t)*. The question to what extent the price volatility of real assets increases during a financial crisis is an open empirical question. There is abundant evidence of increases in the volatility of stock prices during financial crises, but the volatility of equity prices may change (e.g. as a consequence of changes in leverage) although real asset volatility remains unchanged.

3.2.2. The Real Effect of Financial Crises

Financial crises usually impair the functioning of debt markets and may affect the willingness of financial intermediaries to supply credit. A number of studies present evidence supporting the view that credit shocks that emerge in the financial sector adversely affect the real economy on both the aggregate- and firm-level perspectives.[54] The existing evidence at the firm level mainly focuses on how distressed financial sectors affect firm capital investment and equity valuation, and such influence is different to firms that rely on various financing sources. Chava and Purnanandam (2011) document that bank-dependent firms' equity valuation are significantly reduced than others with similar firm characteristics due to unanticipated shocks experienced on suppliers' capital. This is consistent with the BSST, which suggests that firms that rely on a bank lending for their borrowing find it difficult and/or expensive to replace that source of borrowing during the financial crisis, and especially

[54] At the aggregate-level, Rajan and Zingales (1998) shows how the dependency on external financing has different impact on sectors' growth. Kroszner, Laeven, and Klingebiel (2007) provides evidence that a sector more reliant on external funds would experience a greater contraction of value added during a banking crisis.

costly to bank-dependent firms (Ivashina and Scharfstein (2010)). More generally, Duchin et al. (2010) find that the decrease of investments is more acute for firms reliant on external financing (not just on bank loans) during the first year of the crisis. This is consistent with the CSST, which suggests that all credit-dependent firms (not just bank-dependent firms) are expected to be more adversely affected. On the contrary, Kahle and Stulz (2013) document that firm capital expenditures are very similar during the crisis irrespective of their funding strategy, which supports the DST.

Overall, the literature so far has no conclusive argument on which view is the most relevant explanation to the 2007−2009 crisis affecting real outcomes on firm equity valuation or investment. Our study is related to the above literature, but our distinctive contribution is to examine the impact of financial crises on *corporate default risks*. In this paper, we use cross-sectional variation of changes in a forward-looking measure of default risks, the Distance-to-Default (DD) before and during the crisis as a way to shed light on the alternative explanatory power of the above three theories.

Based on these facts, we hypothesize that during financial crises : (i) if BSST holds, bank-dependent firms experience a greater increase in default risk (decrease in DD) than otherwise equivalent firms with no bank dependence, (ii) if CSST holds, all credit-dependent firms experience a greater decrease in DD than otherwise equivalent firms with no credit dependence and, (iii) if DST holds, all firms, irrespective of their financing structures, experience a similar proportional increase in their default risks.

3.2.3. Default Risks and Financial Crises

To study the extent to which distress in the financial sector spills over to default risk increases in the real economy, and how alternative debt financing sources affect this risk spillover remains largely unanswered.[55] Recent papers examine how debt market frictions affect firm default risks both in theoretical and empirical perspectives. He and Xiong (2012b) develop a theoretical model implying that debt market frictions, raising debt financing costs, would lead to greater credit risks, even in the absence of any constraint on the firm's ability to raise more equity. Chen et al. (2012) propose a theoretical model that captures higher default risks in bad times (debt market illiquidity) than good times. This implies that firms using debt as main financing tools (i.e., credit-dependent firms) are expected to suffer more default risks as compared with non-credit-dependent firms. The above literature addresses debt market frictions arising from illiquidity of corporate bond markets;[56] thus, it may indicate that firms that mainly finance from public debt markets are expected have greater default risks during financial crises. We consider that the implication of such theoretical models can be applied in the case of bank lending frictions, since debt financing costs also increase in bank loan markets, which is consistent with setting of models on capturing debt market frictions. Thus, we may also observe greater credit risks for firms that rely on bank loans. Impaired credit supply increases firms' default risks, while the level of such increase might be different depending funding sources (bank credit and on public debt markets). We empirically test this theory.

To our knowledge, only few papers empirically examine this issue, and their results suggest that bank lending shocks increase default probabilities in non-financial corporate sectors. For example, Khwaja and Mian (2008) state that banks pass their liquidity shocks on small firms therefore increasing default probabilities for such firms, because small firms are unable to compensate their loss by additional borrowing through the credit market, and face

[55] Some recent studies underline the importance of this spillover channel. Chiu, Peña, and Wang (2014) document significant tail risk spillovers from the financial sector to the corporate sector, especially for firms highly dependent on external debt financing.
[56] In particular, extant literature suggests that rollover risk exacerbates the conflicts of interest between shareholders and debt holders, and then increases the possibility of a run on a firm (Morris and Shin (2009), He and Xiong (2012a), and He and Xiong (2012b)).

large drops in overall borrowing.[57] Schnabl (2012) find that the liquidity shock in bank lending affects the allocation of credit across firms therefore affecting firm outcomes by increasing loan default and decreasing firm survival on Peruvian firms. Thus, not only does a liquidity crunch reduce overall lending to firms, but it also makes it more likely for the affected firms to enter into financial distress. The above empirical evidence indicates that liquidity shocks tend to make bank-dependent firms closer to their default barriers. Our study also identifies the bank lending shocks on default risks in the corporate sector, but we extend this research strand in two ways. First, the above literature only investigates the bank lending supply effect on firm default probabilities in emerging markets. We, instead, focus on the U.S. market. Second, we consider not just firms that borrow from banks, but all non-financial firms.

3.2.4. Substitution Effect

Evidence suggests that bank-dependent firms suffer higher default risks because of cuts in bank lending, provided they cannot find other financing sources to substitute this financing gap. On the other hand, if bank-dependent firms can easily move from private to public-debt markets, the bank supply shocks may not necessarily increase default risks. We define this flexibility in accessing financing sources the "substitution effect." The empirical results to this effect are mixed. Some studies support that public-debt markets can reduce firms' exposure to drops in the supply of bank lending (e.g., Bernanke (2007), Chava and Purnanandam (2011)),[58] whereas some others highlight the important role of bank credit supply by showing that even large firms with access to the public credit market are still

[57] Large firms are not affected by these shocks because they have alternative financing mechanisms. Notice however that in our paper, we examine whether this effect is stronger for bank-dependent firms after controlling for firm size. Also, they use loan defaults as a proxy for financial distress, while we consider default risk at firm level. Nevertheless, loan defaults should be alike to firm default since the cross-default clauses make it unlikely that a firm can default on one bank but not on another.

[58] Chava and Purnanandam (2011) show that firms able to access public debt markets were not affected by 1998 LTCM crisis. During the crisis period (from August 14, 1998 to September 3, 1998) banks suffered huge losses, but the public-debt market was functioning steadily as suggested by the modest levels of the commercial paper-Tbill-spread.

vulnerable to shocks in bank credit supply by reducing net investments, net debt issuances, and equity valuation losses (e.g., Lemmon and Roberts (2010), Carvalho et al. (2012)).[59]

As far as we know, there is only one study that examines the impact of substitution effect on default risk. Adrian et al. (2012) present a theoretical model and empirical evidence suggesting that the transmission mechanism of financial sector distress to real activity comes from the spike in debt financing premiums, rather than contraction in the total quantity of bank lending.[60] Therefore, even if a firm can access public debt markets to partially offset its financing gap (resulting from cuts in bank lending), spreads (financing costs) on both financing sources both increase at the same time. Increased spreads imply higher default probabilities (Fiore and Tristani (2012)). In summary, previous literature does not support the substitution effect, given the behavior of credit spreads. However our distinctive contribution is provide direct evidence on this issue based on the distance-to-default measure.

3.3. Identification Strategy and Empirical Methodology

The goal of our empirical analysis is to test whether the variation of financing source influences default risks in corporate sectors by examining firms' distance-to-default (DD) during 2007−2010 crisis, and at the same time examine which transmission channels (bank supply shock theory, credit supply shock theory, and demand shock theory) is more relevant to explain the impact of financial crises on the real economy. To do so, we outline our empirical strategy as follows.

3.3.1. Identification Strategy

We examine the time-series and cross-sectional heterogeneity of DD across firms.

[59] The reason is that when several firms want to access public-debt markets at the same time, in response to a reduction in bank financing, the supply of new funds will not be able to accommodate this demand and the cost of raising funds in public markets would increase accordingly.

[60] Their paper shows that during 2007−2009, there was a 75% decrease in loans but a two-fold increase in bonds. However, the costs of both financing channels show a steep increase by four-fold increase for new loans, and three-fold increase for bonds.

Specifically we propose a strategy to classify a firm based on its dependence of accessing bank and/or public-debt market and the strength of its bank relationships prior to the onset of the crisis.

3.3.1.1. Cross-Sectional Classification: Source of Debt Financing

There are two main debt financing sources, from banks or from public-debt markets (such as, corporate bonds, commercial paper, etc.). A firm may rely on one borrowing channel, both, or none. We define firms as "Credit-Dependent Firms" (henceforth called CDF), when there is evidence that they obtain funds from banks and/or public debt markets. We denote firms as "Non-Credit-Dependent Firms" (henceforth called NCDF) when there is no such evidence. This identification strategy is designed to test the credit supply shock theory (CST). If increases in default risks are significantly higher for CDF than for NCDF, then the evidence is not inconsistent with CST.

Furthermore, we examine the bank supply shock theory (BSST). In doing that, we partition CDF firms into three subgroups based on their dependence on bank loans: (1) firms with strong dependence on bank loans (named "strong-bank-dependent firms" henceforth), (2) firms with weak dependence on bank loans (named "weak-bank-dependent firms" henceforth), and (3) firms with no bank dependence but with public debt dependence (henceforth called PDD). The rationale is that if changes in default risks across all CDF firms are not significantly different, this fact supports the CSST; on the other hand, if default risk increases more in the case of bank-dependent firms, this fact supports BSST.

In order to test the substitution effect, we divide the bank-dependent firms into two subgroups: one has only bank relationship and the other has bank relationship and also access to public debt market. Therefore strong-bank-dependent firms (weak-bank-dependent firms) are partitioned into two subgroups as (1) SB (WB): only has access to bank loans and (2)

SBPD (WBPD): has both access to bank loans and public debt market. The rationale is that if the substitution effect holds, then the increase of default risks for SBPD is expected to be less than SB, because firms included in the former group can access public debt markets to mitigate the adverse impact of banking lending contraction. In summary we classify firms into six mutually exclusive subgroups:

(1) NCDF: Non-credit-dependent firms (neither bank nor public-debt dependence);

(2) SBPD: Strong-bank-dependent and public-debt-dependent firms;

(3) SB: Strong-bank-dependent but without public-debt dependent firms;

(4) WBPD: Weak-bank-dependent and public-debt-dependent firms;

(5) WB: Weak-bank-dependent but without public-debt-dependent firms;

(6) PDD: Public-debt dependent but without bank-dependent firms.

By construction, CDF includes subgroups of 2 to 6.[61]

This identification strategy has four features. First, firms included in SBPD and WBPD have a wider choice of financing options available. Second, firms included in SBPD and SB are more sensitive to banks' lending decisions because they have the strongest bank relationship. Third, firms included in PDD have exposure to credit markets but no bank relationship, making it possible to examine the theory of credit supply shock.[62] Fourth, firms included in NCDF are assumed to finance by themselves through internal funds or equity markets.[63]

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[61] Previous papers identify bank-dependent firms when they do not have credit ratings. We argue that this identification rule is too crude and our strategy reflects a more sophisticated approach. We rely on actual syndicated loan data (provided by banks) to identify bank-dependent firms.

[62] As far as we know, there is not an experimental design in the extant literature that could discriminate the credit supply shock from bank supply shock as our design does.

[63] No doubt, a firm's issuance of additional equity, when other financing sources are barely available,

We evaluate a firm's dependence on banks by examining their repeated contracting between firms and banks which correlates with a strong bank-borrower relationship. In particular, we consider a firm of having strong relationship with banks when the firm borrows two or more than two loans with the same U.S. lead bank in the five years before the end of the second quarter of 2006 in line with Duchin et al. (2010) and Kahle and Stulz (2013). We consider a firm as having weak bank relationship when it borrows from banks but does not qualify as a strong-bank relationship.[64] Furthermore we use the credit rating as an indicator of public-debt dependence (see Chava and Purnanandam (2011)).

3.3.1.2. Time-Series Classification: Five Time Phases between 2006Q2 and 2010Q1

We are interested in examining the time-series changes in default risks. Specifically we focus on the period between 2006Q2 and 2010Q1 since it covers the 2007-2010 financial crisis as well as one year before this crisis. We follow Kahle and Stulz (2013) and divide this period into five phases: (1) pre-crisis (2006Q3−2007Q2); (2) first-year crisis (2007Q3−2008Q2); (3) pre-Lehman (2008Q3); (4) post-Lehman (2008Q4−2009Q1); (5) last-year crisis (2009Q2−2010Q1).The first phase (pre-crisis) includes one year before the beginning of subprime crisis (usually dated around July, 2007). The second phase (first-year crisis) covers several extreme economic events, such as the starting period of the subprime crisis and the Bear Stearns bankruptcy. Our empirical analysis will focus on the first year of

impacts its default risk, since it can replace debt with equity. Our sample only includes publicly traded firms, which all have access to equity markets. To take into account how equity finance affects our conclusions, we examine time-series changes in net equity issuance (defined as aggregate equity issuance minus aggregate equity repurchase dividend by lagged assets) across groups based on our matched sample. The results (not presented here but available under request) show no material differences between NCDF and any subgroup of CDF in terms of their time-series changes (crisis periods versus pre-crisis) in the net equity issuance, except for a few cases in the last-year crisis period. Therefore, the use of equity financing does not seem to be relevant to our study before Lehman's bankruptcy. We leave for future research, though, the analysis of the impact on default probabilities of the variation of external equity dependence.

[64] To establish bank-firm relationships, we employ the LPC Dealscan database, which has been used in related studies (e.g., Dennis, Nandy, and Sharpe (2000), Bharath, Dahiya, Saunders, and Srinivasan (2011), Kahle and Stulze (2013), and Norden, Roosenboom, and Wang (2014)).

the crisis because it is more plausible that the shock to credit during that year is not caused by demand shocks in the corporate sector (see Duchin, Ozbas, and Sensoy (2010), and Kahle and Stulz (2013)). The third phase (pre-Lehman) contains the events surrounding Lehman's bankruptcy (September 15, 2008). The fourth phase (post-Lehman) covers two quarters after Lehman's bankruptcy. The fifth phase (last-year crisis) is the final stage of the acute phase of the crisis and goes from April 2009 to March 2010. By this time, the panic subsided, the stock market rebounded from its lowest level, and credit spreads declined from their peaks.

3.3.2. Empirical Methodology

In this section, we present our choice for the measurement of default risks. Next, we show how to apply the "difference-in-differences" method in testing whether and how costly financing frictions are for borrowers' default risk by exploiting the differences of changes in default risk indicators. Subsequently, we present the propensity score matching mechanism in selecting the control group to be used in difference-in-differences method.

3.3.2.1. Measuring Default Risk: Distance-to-Default

There are many possible measures of default risk available in the literature based on different firm's characteristics such as size, leverage, stock market performance, stock volatility and other risk-related variables. We choose to measure default risk by using distance-to-default since it is widely used as an indicator of default risk for non-financial corporations in the literature (see Goyal and Wang (2013), Bharath and Shumway (2008), Chava and Purnanandam (2010)) and also because its non-linear functional form which might contain additional information on the interaction of the different risk-related variables. The Distance-to-Default (DD) is the number of standard deviations that a firm's asset value is away from its default threshold at the forecasting horizon. Therefore it is inversely related to default risk. This default risk measure is based on Merton (1974), and there are several alternative approaches for estimating the relevant parameters (asset value and asset volatility). We compute DD following the well known Moody's KMV approach as:

$$\mathrm{DD} \equiv \frac{\log\left(V/B\right)+\left(\mu-\sigma_V^2/2\right)T}{\sigma_V\sqrt{T}} \tag{8}$$

where V is a firm's total asset value, B is a firm's face value of debt, σ_V is the volatility of a firm's asset return, μ is an estimate of the expected long-run return of a firm's asset return, and T is the maturity of a firm's debt. The details of the estimation procedure are explained in Appendix A. We calculate DD at monthly frequency by implementing one-year window rolling and updating it month-by-month.

3.3.2.2. Difference-in-Differences Estimations

The Difference-in-Differences (Henceforth, called DID) measure is defined as the difference between changes in our key variable, which is DD,[65] across groups and over time. This method allows us to compare the *changes* in DD with respect to a reference period (in our case the pre-crisis period) across groups and over time rather than compare the *levels* of the variable across the treatment and control groups. In doing so, we control for the fact that the levels of DD in the treated and control groups could be different because of fundamental differences between them. We define the DID$(g,k)_t$ measure for groups g and k in period t as follows:

$$\mathrm{DID}\left(g,k\right)_t = \frac{\sum_{i=1}^{I}\left(X_t^{i,g}-X_{\text{pre-crisis}}^{i,g}\right)}{I}-\frac{\sum_{j=1}^{J}\left(X_t^{j,k}-X_{\text{pre-crisis}}^{j,k}\right)}{J} \tag{9}$$

[65] Several recent studies also use difference-in-differences method and claim that the DID method is preferable to multivariate regression approach. The reason is that it is hard to avoid endogeneity problems when using regressions (see Chava and Purnanandam (2011), and Kahle and Stulz (2013)).

where $X_t^{i,g}$ is the average DD for firm *i* in group *g* which contains *I* firms, over the period *t=1,2,3,4*, where *t=1* corresponds to the first-year of the crisis, *t=2* to the pre-Lehman period, *t=3* to the post-Lehman period and *t=4* corresponds to the last year of the crisis; $X_t^{j,k}$ is the average DD for firm *j* in group *k* which contains *J* firms. The DID$(g,k)_t$ refers to the difference of the average value of the time-series changes of DD between group *g* and *k* in period *t*. Therefore, by construction, this is a cross-sectional measure. We use the one-sided Wilcoxon rank-sum test in assessing the statistical significance of DID. This test is a nonparametric alternative to the standard two sample t-test, and is more appropriate than the standard test because the distribution of changes in DD is not normally distributed.

3.3.2.3. Propensity Score Matching

In DID estimators, we need to obtain similar groups of treatment (e.g. CDF) and control (e.g. NCDF) subjects by matching observable firms' risk characteristics on their propensity scores. Pairs of matched firms are similar along meaningful dimensions such as size or leverage. However, for obvious reasons, we do not include the DD into these dimensions.[66]

We use the Propensity Score Matching (Henceforth, called PSM) method for the matching exercise (see Rosenbaum and Rubin, 1983). In doing so, we adjust for selection bias. The propensity score is the probability of belonging to the treatment group (in our case CDF) given a vector of observed variables. This propensity score is estimated from a probit regression. If we take firms with the same propensity score and divide them into two groups, the groups will be approximately balanced on the variables used to predict the propensity score. There are many matching algorithms available: Nearest Neighbor (NN), Caliper Matching (CM), Stratification and Interval (S&I), Kernel and Local Linear (K&LL) among

[66] We do not match on DD (the variable to be examined in difference-in-differences estimations) since that would bias us against finding any differences.

others. The basic method is the NN in which a case in the control group is matched to a treated case based on the closest propensity score. We choose the improved CM method where a case in the control group is matched to a treated case based on a tolerance level on the maximum propensity score distance (caliper), to avoid the risk of bad matches. The selection process could be done without replacement, (subjects are not returned to the sample after being pair-matched) or with replacement (one identical control firm could be matched into multiple treated firms). Our baseline analysis is based on PSM without replacement, but we also provide the results of PSM with replacement in the robustness test section.[67] We set the difference between propensity scores of the treated unit and the control unit to be within the caliper ±2.5%.[68]

In PSM, we construct two subsamples in a similar dimension on a set of firms' characteristics. The control variables are associated with firms' default risk. Specifically, we choose:

(1) Size: the logarithm of book value of assets;

(2) Leverage: the ratio of debt to assets;

(3) Volatility: the annualized standard deviation of daily equity returns for a year;

(4) Past-Ret: the annual stock return over the past one year;

(5) Cash/Asset: the ratio of cash to assets;

(6) NI/Asset: the ratio of net income to assets;

(7) Industry effect (Fama-French 38 industry dummies)

[67] One problem of "without replacement" is that many of the subjects in the dataset are discarded, reducing power and generalization. Thus we implement PSM "with replacement" by setting maximum number of multiple matches are up to two, three, or four. The details are provided in robustness section.
[68] Our results are robust to changing the caliper into ±5% and ±10% as shown in the robustness test section.

These variables are motivated by the hazard model literature, and are among the most important determinants to default risks (etc., Shumway (2001), Chava and Jarrow (2004), and Campbell et al. (2008)). We control for firm size because larger firms are more diversified, which reduces operating risks, and so they face lower default risk than smaller firms. Leverage is included since the higher the debt (high leverage) the higher the chances of default. Volatility implies the probability of a firm's asset value being below the default boundary, so the higher volatility the higher the uncertainty and therefore the higher the default probability. Low past equity returns should be related with increases in default risk. We include the ratio of cash to assets because this variable reflects a firm's ability to pay its financial debt obligations. Profitability (proxy of the ratio of net income to assets) is considered because a profitable firm should be less likely to default. Finally, we allow for industry effects by means of dummy variables.

3.4. Data

We study all publicly listed non-financial firms in the U.S. market during the period of 2006Q3−2010Q1. We perform a set of data sample selection rules. First only non-zero leverage firms are chosen for two reasons: (1) default risks (proxied by distance-to-default in this study) can only be measured when leverage is not zero, and (2) only leveraged firms have obligations to pay for debts, thus causing uncertainty of defaults. We remove from our sample firms with zero debt in the second quarter of 2006. Second, we exclude financial firms (SIC 6000-6999), utility companies (SIC 4910 and 4940) and firms in the public sector (SIC 9000-9999). Third, we choose firms with available daily equity prices and quarterly balance sheet information in the CRSP and COMPUSTAT database.[69] We lag all accounting information by 3 months because of reporting delay and substitute missing accounting data with the most

[69] We obtain information of daily equity prices and outstanding shares from CRSP, and select information of total assets, debt in current liability, long-term debt, and outstanding shares (if missing in CRSP) from COMPUSTAT at quarterly frequency.

recent observation prior to it. The final number of firms chosen is 3,158. We identify firms as public-debt dependent firms when they have credit ratings at the end of June 2006. The information of firms' rating is collected from Compustat S&P 500 long-term ratings.

3.4.1. Bank Loans

We collect bank loans data beginning at the year of 1986 from DealScan Loan Pricing Corporation (LPC) database. The LPC provides detail information for the syndicated loan market. Given that our attention is on public firms, we merge DealScan and Compustat by using the Compustat-LPC link file provided by Michael Robert (Chava and Roberts (2008)), to distinguish public firms from private ones.

The data shows that there was a remarkable decline in bank lending during 2007−2010. Figure 5 (Panel A, public firms), shows that newly issued syndicated lending within U.S. market started to fall since June, 2007, and went down to its lowest level on January, 2009. Over this period, on a monthly basis, it dropped by 77% (from 178 to 40) in terms of the number of deals, and decreased by 96% (from $162 to $6 billion) in the average amount. Since then, a slight increase appeared, but the average level was much lower than the pre-crisis level. For example, the number (amount) of the issuance of new loans on average was 148 ($103 billion) per month over the year before June 2007, while it was only 58 ($29 billion) in year 2009. This decrease of bank lending is observed not only in the case of public firms, but also for all firms (both private and public firms) as shown in Panel B of Figure 5.[70]

[Insert Figure 5 Here]

To evaluate the extent of reliance on bank financing, we use bank loan data at facility-level. We consider a firm to have a strong-bank relationship when it has two or more than two loans

[70] Our result is consistent with the finding in Ivashina and Scharfstein (2010) that syndicated lending, as measured by agreements reported to Dealscan, started to fall in mid−2007 and dropped dramatically in the last quarter of 2008.

with the same lead bank[71] over the five years before the second quarter of 2006 (Kahle and Stulz (2013)) .[72]

3.5. Empirical Results

In this section, we examine whether the variation of financial sources influences default risks during 2007−2010 financial crisis, and which view is more relevant to explain transmission channel from distressed financial sector to real economy sectors: bank supply shock theory, credit supply shock theory, or demand shock theory. Furthermore, we examine the substitution effect on default risks.

3.5.1. DD: Summary Statistics and Preliminary Tests

We compute DD between 2006Q3 and 2010Q1. We use daily equity data and quarterly accounting data to measure DD at the end of each month and update it one month forward.[73] Figure 6 shows the time series of DD for CDF and NCDF firms. The DD for CDF firms was above DD for NCDF firms on average until October 2008 (the first month after Lehman's bankruptcy). Between October 2008 and August 2009, the situation reversed. After that it went back to the initial situation. This result implies that although CDF firms are usually financially healthier than NCDF in normal times, the former tend to suffer higher default risk than the later, during extreme crisis periods.

[Insert Figure 6 Here]

[71] The lead bank is often the administrative agent that has duty to other syndicate members to provide information about borrowers' default situation. As a consequence, observing the connection between lead banks and borrowers gives us useful information to assess the strength of a borrower's bank relationship. We treat loans granted by a parent bank or its subsidiary or branch as loans originating from the same lead arranger (see Ferreira and Matos (2012)).

[72] We also account for activities of merges and acquisitions when identifying loans granted from an identical lead arranger. It is better to provide an example to illustrate this point. For instance, BANC ONE CORP merged with JPMORGAN CHASE & CO in 2004. If a firm has a lead bank BANC ONE CORP before 2004 and has a lead bank JPMORGAN CHASE & CO between 2004 and 2006Q2, we consider the firm as having as a lead bank JPMORGAN CHASE & CO.

[73] The quarterly time series data is linearly interpolated between quarterly reporting dates and turns out to be at daily frequency.

Table 6 contains the basic statistics of DD and some preliminary tests over the four time periods: (1) pre-crisis (2006Q3−2007Q2); (2) first-year crisis (2007Q3−2008Q2); (3) pre-Lehman (2008Q3); (4) post-Lehman (2008Q4−2009Q1); and (5) last-year crisis (2009Q2−2010Q1) and across the two main groups (NCDF and CDF) as well as the five CDF-based subgroups (SPBD, SB, WBPD, WB, and PDD). Our tests are conducted on a panel where the risk measures are computed for each firm and through five time periods. In the following we aggregate our firm-month sample into firm-period sample by averaging all monthly DD for each time period.

We observe a significant decrease in DD (increase in default risk) in the first year of the crisis in comparison with the pre-crisis period in all cases, excepting the PDD group. Therefore all NCDF firms and most CDF firms (excepting rated firms without bank dependence) become closer to default. The decrease in DD was slightly higher in the case of CDF firms than in the case of NCDF firms, 16.5% versus 14.4%. However the differences across CDF subgroups are more marked, from 22.8% in the case of unrated firms strongly dependent on bank financing (SB) to 5.2% (and not statistically significant) in the case of PDD.

[Insert Table 6 Here]

The preliminary evidence during the first year of the crisis seems to be more supportive of the impaired access to banking financing theories than alternative theories based on a demand shock. Theories based on a an overall credit crunch are not so clearly supported by the data because rated firms without banking connections did not become closer to default during this period.[74]

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[74] In agreement with the discussion in section 2.1, the data indicates that the reason of the decrease in DD is because there is an increase in asset volatilities in most cases during the first year and in subsequent periods in comparison with the pre-crisis period. In the first year the stronger increase was

If we compare the changes in DD from the pre-crisis to the last-year of the crisis, we observe a strong decrease in DD across the board ranging from 56% (SBPD) to 41% (PDD) all of them statistically significant. Again the CDF group experiences a slightly bigger decrease (52%) than the NCDF group (49%) although much more marked differences appear across CDF subgroups. The evidence here is less clear cut than before.

Finally we discuss briefly the most acute crisis period, the Post-Lehman versus Pre-Lehman (2008Q3). In this period the decrease in DD is stronger and very significant in all cases both for CDF firms (67%) and for NCDF firms (57%). Specially marked is the increase in default risks for PDD (71%) and also for rated firms with strong (69%) or weak (73%) bank dependence. An overall credit crunch should perhaps be more consistent with these facts.

3.5.2. Full Sample Analysis

Based on the full sample, Table 7 reports results of time-series changes in DD by subtracting from any crisis period its value at the pre-crisis level. Thus, negative differences indicate that the default risk during crisis period increased as compared to its pre-crisis level. The results are reported in Panel A for first-year crisis, in Panel B for pre-Lehman, in Panel C for post-Lehman, and in Panel D for last-year crisis. For a given time period, we present a cross-sectional analysis. Model 1 to 7 refers to results based on subsamples of NCDF, CDF, SBPD, SB, WBPD, WB, and PDD respectively. The cross-sectional differences of time-series changes are denoted as DID in the table, which is computed by subtracting the average value of time-series change of NCDF from the value of CDF (or any subgroup of CDF). As a result, a negative DID implies that the default risk of CDF (or any subgroup of CDF) is larger than it of NCDF at a given time period. We use the Wilcoxon two-sample test to evaluate the statistical significance of DID measure as mentioned in the section 3.

for the SBPD and SB groups. Detailed results are available on request.

[Insert Table 7 Here]

To highlight the economic impact of changes in DD, we map them to changes in default rates through an empirical default distribution.[75] We describe how to generate the empirical default distribution in Appendix B.[76] For example, in the period of 2007Q3-2009Q1, the DD decreased by 6.72 and 5.56 for CDF and NCDF respectively. This translates into default probabilities by the increase of 104 basis points for CDF firms and 80 basis points for NCDF firms.

It is worth noting that for CDF firms (Model 2), the DID is negative and significant at 1% level through the whole crisis period, indicating that CDF firms had higher default risks than NCDF firms. This result is consistent with the preliminary analysis in Table 6 in the sense that firms that primarily rely on debt financing are more likely to default in times of credit supply contraction.

We now examine the cross-sectional variation of changes in default risk across subgroups within CDF. Focusing on the first-year of the crisis, SB experienced the largest decrease in DD (-1.89). This translates into an increased default likelihood of about 7 basis points, which is larger than the mapped default rate at the pre-crisis period which was 1 basis point. On the other hand, the decrease in DD for NCDF firms is -0.82, roughly equivalent to an increase in default risk of 3 basis points. This implies that SB firms are more likely to go bankrupt than NCDF firms by a two-fold of the increased default probability. The DID

[75] By construction, the Merton model applies the Normal distribution to calibrate default probabilities. We do not use the Normal distribution to transform DD into default rate, due to the fact that the empirical distribution of defaults has a fatter tail than the Normal distribution (see Crosbie and Bohn (2003)).

[76] For example with DD about 7, the observed default rate over the next year is roughly 7.2 basis points. Goyal and Wang (2013) performs a similar method to calibrate the empirical default probability based on the sample from 1985 to 2006, and show that with an average distance-to-default of about 7, the observed default probability over the next year is approximately 5.9 basis points, which is a little bit lower than our estimation. This difference may be due to the different sample periods (1985-2006 versus 2006-2010 in our case).

measures are significantly negative at 1% level for SB, SBPD, and WBPD, and at 5% level for WB. Thus our results indicate, at the initial stage of crisis, bank-dependent firms suffer more default risks as compared to NCDF firms, and this adverse effect is even higher for firms with strong bank dependence. The evidence of DID on PDD is less clear cut. There is a small positive effect (see Model 7) suggesting that rated firms without bank loan dependence fared better than NCDF firms in terms of default risk during the first-year of the crisis. However the statistical significance is borderline and the economic effect is small. We should stress again that the analysis of the first of year of the crisis is particularly important, because previous literature considers this period as specially well-suited one to examine the impact of financial shocks, because firms' policies are less affected by demand effects at the initial stage of recession (e.g., Duchin et al. (2010), Kahle and Stulz (2013)).

From pre-Lehman to last-year crisis, the SBPD group always experienced the largest decreases in DD, followed by the WBPD group, and then SB group. DID measures for both groups are all negative and significant at 1% significance level. DID measures in the case of PDD are consistently positive over the entire crisis period and significant in three over four periods suggesting that rated firms without banking relationships fared relatively well during the crisis in terms of default risks in comparison with NCDF and other CDF firms.

Overall, we find that default risks increased more for firms that primarily rely on credit financing in comparison with non-credit-dependent firms. However there is an exception in the case of rated firms without bank dependence. In particular, bank-dependent firms (rated or unrated) generally suffer more default risks than other firms. This adverse effect is especially more noticeable for firms with strong bank-borrower relationships. Therefore, the full sample results tend to support bank supply shock theory. Note that the full sample result might not be entirely reliable because of fundamental differences between groups, e.g., leverage. The post-matched sample excludes other factors that are also related to firm's default, and thus provides more reliable evidence. Therefore, we re-examine the analysis based on the matched sample, which balances observable firms' risks characteristics between treatments and controls.

3.5.3. Matched Sample Analysis

In this section, we analyze the results from the matching procedure and DID tests based on the matched sample.

3.5.3.1. Propensity Score Matching

The goal of this exercise is to create matched samples, where two subsamples have similar firms' characteristics that could distinguish high default risk firms from low ones. All accounting and market variables are obtained as of the last quarter accounting information or one year equity market information before the June 2006. To prevent outliers from affecting our results, we winsorize data at 1% and 99% in all analyses.

The summary statistics of control variables are provided in Table 8. We may observe that four variables present remarkable differences of CDF (Panel B) or any subset of CDF (Panel C) against NCDF (Panel A). The CDF firms on average have larger size and leverage, while have lower volatility and cash-to-asset ratio compared to NCDF firms, across statistics of mean and quantiles (25^{th} percentile, median, and 75^{th} percentile).

[Insert Table 8 Here]

Table 9 presents the estimation results of the full sample in Panel A and of the matched sample in Panel B respectively. Model 1 of Panel A shows that differences of CDF firms (in comparison with NCDF firms) are positively associated with firm size, leverage, and net income-to-asset ratio; and negatively associated with equity return volatility and cash-to-asset ratio. The signs of the coefficient estimates on the control variables are as expected. That is, by construction, the magnitude of a firm's external debt financing is positively related to leverage, but negatively related to needs of internal funds (cash); large firms require a larger amount of operating funds, and they probably resort to external sources, and big firms usually have lower equity return volatility.

[Insert Table 9 Here]

We also implement alternative probit regressions by substituting one of the subgroups within CDF (SBPD, SB, WBPD, WB, and PDD) for the entire group of CDF, one-by-one, and report estimation results in Model 2 to 7 of Panel A. The signs of coefficients are consistent with Model 1, although magnitudes are not necessary the same. The values of pseudo-*R-square* are larger for subgroups having rating, but smaller for those without rating. For example the value on SBPD is of 61%, followed by PDD of 56%, then by WBPD of 46%, while it is 36% for SB and 12% for WB. It indicates that those firms' characteristics are able to distinguish CDF firms from NCDF firms especially for CDF firms with ratings.

After PSM, and as expected, estimated coefficients are not significant anymore and values of pseudo-*R-square* drop to 5.2% or lower across all specifications of probit regressions (see Panel B of Table 9). This evidence confirms that, the matched sample is equally balanced on the observable dimensions that might influence default occurrence before the second quarter of 2006.

The Figure 7 shows the distribution of four key firms' characteristics. The left-hand diagrams are distributions of the full sample, and the right-hand diagrams are those of the matched sample. The red line represents the CDF group, and the blue line represents the NCDF group. As expected, in terms of the entire sample, distributions on the variables of size and leverage for the CDF group are located to the right of the NCDF group (see Panel A and B of Figure 7), while distributions on variables of volatility and cash-to-asset ratio are clearly located to the left for the CDF group compared with the NCDF group. After mapping, distributions are now similar for both groups as shown in diagrams on the right-hand side of Figure 7.

[Insert Figure 7 Here]

3.5.3.2. Results of Matched Sample

Table 10 presents the results based on the matched sample. Our focus is the DID estimators for the three crisis periods: first-year (2007Q3−2008Q2), post-Lehman (2008Q4−2009Q1), and last-year (2009Q2−2010Q1).

[Insert Table 10 Here]

During the first-year of the crisis, DID is negative and statistically significant only for strong-bank-dependent firms (Model 2), after controlling a set of variables that are related to firms' defaults. This evidence is consistent with the findings in the full sample, and supports the bank supply shock theory. However, we observe that the DID becomes non-significant for weak-bank-dependent firms (Model 3); and the DID of CDF (Model 1) turns into positive and non-significant. The result of non-significant difference between NCDF and CDF might not be unexpected. In the 2007 credit crisis, the flight to quality might affect equity markets as well and hence hinder equity issuance and make it too costly. This post-matched result further supports the idea that only firms having strong bank dependence experience a significant increase in default risks against their matched firms having no credit dependence. Also, DID of PDD is insignificantly positive (Model 4). This result suggests that rated firms without banking dependence behave pretty much the same as NCDF firms at the initial stage of crisis as far as their default risk is concerned. Therefore, this evidence is inconsistent with the idea of an overall credit crunch being the main channel of transmission of the effects of the financial crisis from the financial sector to the real economy. Furthermore the DID of SBPD and SB (see Model 5 and 6) are both negatively significant at 5% level. This finding highlights that even firms with access to public credit markets are still susceptible to fluctuations in the supply of capital, which is inconsistent with the substitution effect. We should stress again that the first-year result offers more reliable evidence in testing the implications of the theories of impaired access to capital.

Second, at the post-Lehman stage (two quarters after the bankruptcy of Lehman), we observe that DID for the CDF group and for a majority of CDF subgroups is negatively significant at 5% level (Model 1), except for WB at 10% level and for PDD with no significant sign. Thus, this result is consistent with the bank supply shock theory, but does not support the credit supply shock theory. Two largest negative values of DID appear in SBPD (-1.75) and WBPD (-1.73), followed by SBR (-0.96) and they are all negatively significant.

Focusing on last-year of the crisis, as compared to the full sample analysis, of which DID for the CDF group remains negatively significant at 5% level. Across CDF subgroups, we observe DID are only negatively significant for SBPD and WBPD at 1% level. Last-year result indicates that NCDF firms recover more quickly towards their pre-crisis levels of DD.

Furthermore, although we observe that DID estimators are negative across all types of credit-dependent subgroups, the absolute values of DID are systematically larger for strong-bank-dependent firms (Model 2), followed by weak-bank-dependent firms (Model 3), and finally PDD (Model 4), through the whole sample period.

In sum, the results based on the matched sample suggest that, regarding the effect on default risks, the banking supply shock theory is not inconsistent with the data. However the overall credit crunch theory and the demand shock theory are not supported by the empirical evidence.

3.5.4. Substitution Effect

This section provide a test of the substitution effect, which asserts that a firm's availability of switching financing resources between banks and public-debt markets reduces the negative effects of bank lending shocks. We accomplish this by constructing a matched sample of two groups, where both rely on bank loans but only one of them has access to public-debt markets. For example, in terms of strong-bank-dependent firms, we consider SBPD as a treated unit against its control unit of SB. This logic is also applied to the weak-bank-dependent groups. In addition, since we draw inferences based on the strong (or weak) bank dependent subsamples only, this analysis is probably more accurate because it is less exposed to biases created by observable or unobservable differences across firms than the analysis provided in the previous section. Table 11 presents results based on the full sample in Panel A, and based on matched sample in Panel B.

[Insert Table 11 Here]

Regarding to the full sample analysis DID for SBPD is significantly negative since pre-Lehman crisis. This result suggests default risk is material for bank-dependent firms that are capable of issuing public debts in substituting for bank loans. The situation is similar to the case of WBPD, with the measure of DID significantly negative even earlier back to first-year crisis.

The post-matched analysis shows that there is no evidence of economically or statistically important differences to strong bank-dependent firms, irrespective of their capabilities of accessing to public-debt markets. In the case of weak bank dependent firms, DID are even negatively significant at 10% level after Lehman's bankruptcy.

Overall this finding does not support the substitution effect. In other words, the data supports the notion that the public-debt market plays a limited role in offsetting the cost of large funding aggregate shocks over the period 2007−2010.

3.6. Robustness Tests

It is possible that the post-matched analysis results would be different if we use different settings in the Propensity Score Matching. For robustness, we implement PSM with replacements and PSM under alternative settings of the nearest neighbor caliper. Because of some concerns (described in more detail later), we also re-examine our baseline analysis by using three adjusted samples: (1) we exclude speculative-grade firms from our entire sample; (2) we exclude small-size firms from NCDF subsample; (3) we use the whole sample (instead of NCDF) as control groups in the matched sample analysis. The detailed results for the robustness tests are not reported here, but are available upon request.

3.6.1. PSM with Replacement

In the baseline analysis, we implement PSM "without replacement", referring that one treated firm is matched by one control firm. The disadvantage of this technique is that the sample size could be very small, losing statistical power and generalization. In PSM "with replacement", multiple treated firms are matched to one identical control firm, and thus we have a larger sample.

We use several alternative matched samples, which are built under replacement with maximum numbers of treated firms to one control firm by up to 2, 3, and 4.[77] We find that these supplemental analysis (PSM with replacement) also supports the role of the stronger bank relationship (SPBD and SB) resulting in higher default risk at the initial stage of crisis. The group WBPD seems to behave slightly different during the first-year crisis as compared

[77] In the baseline analysis, the maximum number of treated firms to one control firm is 1.

with our main analysis. The result shows that even the groups with weak bank dependence also suffers more default risk. For the extended analysis on the substitution effect, we find that results are not materially changed in comparison with the baseline analysis by showing that DID is not significant in most of cases for the strong bank relationship group.

3.6.2. PSM on Alternative Calipers

We redo the matched analysis by changing the parameter of nearest neighbor caliper in exercising PSM to ±5% and ±10%. Overall there are no material differences in comparison with the baseline specification.

3.6.3. Excluding Speculative-Grade Firms

In a time of crisis, speculative-graded rated firms have a hard time accessing alternative sources of capital in public-debt markets. The result of the limited role of public-debt markets to offset the adverse outcome during financial crisis can be affected by the inclusion in our sample of a number of firms with speculative-grades. This might bias the analysis. To improve the robustness, we discard firms with speculated-grade ratings (lower than a BBB-rating as rated by Standard & Poor), and re-examine all tests based on the new matched sample. We find that the result is similar to previous results, and in some tests, with a stronger negative DID measure, which gives additional support to our point about public-debt markets during financial crisis.

3.6.4. DealScan LPC Bias

It has been pointed out by some authors that DealScan LPC only reports bank loan deals for large firms. It is possible that small firms are also bank-dependent firms, but are not properly represented in our sample. We deal with this issue in two ways. First, we control for firms' size in the baseline analysis. Second, we exclude small firms from NCDF group (less than the median of firms' sizes within NCDF group). The result still favors the bank supply shock theory in the first-year crisis period, given that the DID measure remains negatively significant.

3.6.5. Using the Whole Sample as the Control Group

In the baseline matched sample analysis, we consider NCDF firms as control units. One concern is that the result might be biased because we do not account for some other unobservable variables that may cause increases in default risk for bank-dependent firms (SBPD and SB) and decreases in default risks for PDD. To address this concern, we use the whole sample (excluding treated firms) as the control group. We find that DID remain negatively significant for strong bank-dependent firms at 5% level. This result further supports the bank supply shock theory.

3.7. Conclusion

This paper examines the impact of the alternative financing sources (banks, debt markets) on the default risks of non-financial firms listed in the U.S. stock market during the crisis of 2007−2010. We compare empirically the relative merits of the three most popular explanations of the transmission channel of shocks originated in the financial sector, in explaining changes in the default risk of real-economy firms. These explanations are the bank supply shock theory, the credit supply shock theory and the demand shock theory. We show that, during the 2007−2010 financial crisis, firms closely linked to banks suffered increases in default risks significantly higher than similar firms which are not dependent on bank financing. These results are robust to a number of alternative specifications. We also show that rated firms unrelated to banks behaved very similarly to unrated firms with no banking relationships as far as their default risk is concerned.

Overall our results tend to support the bank supply shock theory as the one more consistent with our data. Therefore policy measures such as the Troubled Asset Relief Program (TARP), which are designed to alleviate problems in the banking lending channel, may also have a positive effect on the default risk of non-financial firms that are especially dependent on bank financing. However we do not find evidence supporting the credit supply shock theory because in our sample rated firms without bank dependence behave pretty much the same as firms having no debt financing sources. A word of caution is in order. We use data reflecting the impact of many policy actions during the crisis and therefore we cannot say what the effect on default risk of banking dependence would have been without these policy actions.

Our results may have potential policy implications. Since the default risk of non-financial firms is related with their degree of funding dependence from banks, instability in the banking sector and a subsequent impairment in the lending channel might have a sizable impact in the credit quality of many corporate sectors. As a result, regulators should take into account this aspect of the transmission of the risk of default, from the banking sector to the real economy, when designing policies to stabilize the banking sector.

Appendixes

Appendix A. Estimating Distance-to-Default

The Moody's KMV model is closely related to the method proposed in Black and Scholes (1973) model. The basic idea is to consider the fact that equity can be viewed as a call option for which the underlying asset is a firm's asset value and the strike price is equal to the face value of a firm's debt. A firm's market value of asset is assumed to follow a geometric Brownian motion of the form:

$$dV = \mu V dt + \sigma_V V dZ, \tag{A1}$$

where V is the total value of a firm, μ is the expected continuously compounded return of V, σ_V is the volatility of a firm's value, and dZ is a standard Brownian motion. With these assumptions and under the Black and Scholes (1973) model, a firm's market value of equity, V_E, can be expressed as a function of a firm's total value as:

$$V_E = VN\left(d_1\right) - Be^{-rT} N\left(d_2\right), \tag{A2}$$

where,

$$d_1 = \frac{\ln\left(V/B\right) + \left(r + 0.5\sigma_V^2\right)T}{\sigma_V \sqrt{T}}, \quad d_2 = d_1 - \sigma_V \sqrt{T},$$

B is the face value of a firm's debt, r is the risk-free rate, T is the forecast horizon, and $N(.)$ is the cumulative standard normal distribution.

In our exercise, we compute V_E as the product of a firm's outstanding shares and its current stock price, consider T as one year, and treat B as the debt in current liabilities plus one-half of long-term debt. This is consistent with the usual way that has been applied by many literatures. The two remaining variables in the Black-Scholes equation – the total asset value of the firm, V, and the volatility of the firm value, σ_V – are estimated through an iterative procedure following the method proposed in Vassalou and Xing (2004). At the beginning, σ_V is estimated as the annualized standard deviation of a firm's asset returns, using daily data of the summation of the market value of equity and the face value of debt over the past one year. This serves as an initial estimate of σ_V, and together with the market value of equity and other inputs, equation (A2) is used to find daily values of V. With the estimated values of V, we generate new estimated of σ_V by using the implied log-returns on assets. The new estimate of σ_V is put into the next iteration until the difference of values of σ_V from two consecutive iterations is less than 10^{-3}. Then we take the final estimated σ_V and its implied V. We compute the drift μ by calculating the mean value of log-returns of V. With these estimated values, the distance-to-default can be calculated based on equation (1).

Appendix B. Empirical Mapping between Distance-to-Default and Default Probability

We map distance-to-default into empirical default probability similar to the mapping technique used in Goyal and Wang (2013). For each firm at the end of a given month, we compute the DD over the past one year. Then we sort firms into ten bins based on DD. We consider a firm's default over the next year if it is bankrupt or liquidated (delisting codes: 400, 572, 574 in CRSP) (see Dichev (1998)). The empirical default rate is estimated as the ratio of the number of defaults to the number of firms in a given distance-to-default category. This results in an empirical mapping between distance-to-default and annual default frequency. We re-estimate this distribution every month forward over July 2006 and March 2010. Finally we average default probabilities over this period, and it gives us the distribution of default rates as a function of DD.

CHAPTER 4

Do Financing Sources Affect Rollover Risk Effect on Default Risk?

4.1. Introduction

Rollover risk arises from firms may face difficulty in rolling over maturing short-term debt or have to refinance maturing debt at high credit risk (Diamond 1991) or high liquidity premium (He and Xiong 2012).[78] Default risk represents the likelihood of firms' insolvency. Rollover risk is interacted with default risk, as witnessed in the financial crisis of 2007-2009, which demonstrates that deterioration in debt market liquidity caused severe financing difficulties for many firms, in turn exacerbating their default risk.

Recent theoretical literature argues that rollover risk could serve as an additional source of credit risk, because it increases the possibility of a run on the firm (see Morris and Shin, 2009), and exacerbates the conflicts of interest between shareholders and debt-holders (He and Xiong, 2012), which in turn forces equity holders default at a higher fundamental firm asset value. The key implication of these theoretical models highlights the notion that rollover risk exacerbates default risk. We called this *rollover risk effect* in this study.

The empirical evidence on testing rollover risk effect is at its early stage. As far as we know, only one published paper by Gopalan, Song, and Yerramilli (2013) offers strong support that firms that experience a large increase in rollover risks are likely to experience a more severe deterioration in credit quality. There are some other working papers engage in empirically testing such effect as well.[79] However, the extant studies only unveil some parts of the rollover risk effect due to limitation of the sample they used. Their samples are restricted to firms that have credit ratings, bond spreads, or credit default swap spreads. We

[78] Diamond (1991) show that firms face difficulty in rolling over maturing short-term debt, especially at the time that refinancing coincides with a deterioration in either firm fundamentals or credit market conditions.
[79] See Chen et al. (2012), Hu (2010), and Valenzuela (2011).

argue that it is important to study to firms that have not been contained so far, and this is especially for unrated firms, which is usually considered as bank dependent firms, because they are represent of almost two-third of firms in the U.S. context.[80] We aim to provide the most comprehensive empirical study of understanding rollover risk on default risk.

This paper studies the impact of rollover risk on default risk by answering two main questions. (1) Do firms with higher rollover risk experience a larger increase in firms' overall default probability? (2) Do financing sources affect the effect of rollover risk on default risk? Although financing sources, debt maturity, and default risk are mutually correlated as highlighted in literature, extant studies only focus on the relationship on any two of them,[81] but not on all of them in the unified notion. To our best understanding, we are the first study providing new empirical evidence on to what extent that financing sources drive the effect of rollover risk on default risk.

In particular, we ask whether being bank dependent firm has larger rollover risk effect than non bank dependent firms (i.e., public debt dependent firms). The reason we focus on the two types of firms is because they are essentially different in many ways, which may disproportionally drive rollover risk effect on credit risk.

Bank dependent firms find more difficult to borrow long-term debt financing, have low debt capacity, facing greater liquidity risk that they cannot refinance at reasonable costs (see Carey et al. (1993), Lemmon and Zender (2007), Diamond (1991), and Mian and Santos (2011)). All these attributes make such type of firms have higher rollover risk. For a firm with high level of rollover risk, it is likely we can find rollover risk effect on default risk for that

[80] As shown in Section, our sample contains approximate 60% of firm-year observations on bank dependent firms, and 40% firm-year observations on non bank dependent firms (i.e., public debt dependent firms).

[81] For example, Chiu, Pena, and Wang (2014) provide empirical evidence showing that financing sources have differential impacts on default risk by documenting that firms that depend on bank loans as main financing sources tend to suffer more default risk than firms that use public debts as main financing sources in the 2007-2010 crisis. Barclay and Smith (1995) find that overall a firm's debt maturity is positively correlated with credit risk for rated firms, whereas the evidence for nonmonotonicity is driven solely by the unrated firms in the sample.

firm if this effect indeed exists. In contrast, if a firm's rollover risk is slim, there is no way we can find rollover risk on default risk for that firm. As a result, we hypothesize that the rollover risk effect is stronger for bank dependent firms compared with public debt dependent firms.

We investigate industrial firms in the U.S. market over the period between 1986 and 2011. We follow Gopalan et al. (2013) by using first difference regression, to eliminate that the firm-specific fixed effects, of which the dependent variable is the change in default risk, and the main independent variable is the rollover risk variable. We also control many relevant default risk factors besides rollover risk variable.[82]

We proxy for default risk with the expected default frequency (EDF) based on Merton's model as the main default risk measure because of a number of advantages. EDF is a continuous, "absolute" measure of default risk that changes over the course of the credit cycle, reflecting the *changes* in the level of default risk, which is exactly we want to capture in this study.[83] Furthermore, computing EDF only requires stock price and accounting information, where both are commonly available, and thus it allows us to measure default risks for many firms, rather than restrict to a certain group of firms. We also compute the distance-to-default (DD) and use credit ratings provided by rating agency as alternative default risk measures, and the results are consistent with our main results.

We measure rollover risk variable by computing the amount of the firm's long-term debt outstanding at the end of year *t-1* that is due for repayment in year *t*. The variable is very suitable in studying the rollover risk effect as suggested in Gopalan et al. (2013) and Almeida, Campello, Laranjeira, and Weisbenner (2012); in that, the variable only depends on the past long-term debt maturity decisions made by the firm, and hence, is less likely to be correlated

[82] They are: (1) *Size* using Log(Total assets), (2) *Leverage* using Total debt/Total assets, (3) *Interest coverage*, (4) *Profitability* using Operating income/Sales, (5) *Tax*, (6) *Market to book* representing growth opportunities, (7) *R&D*, (8) Idiosyncratic volatility (denoted as *Idiovol*) representing operating risk, (9) *Tangibility*, and (10) *Cash*. Detailed definitions of all these variables and economic rationales are provided in Section 3.

[83] On the contrary, credit ratings reflect "relative" rankings of credit risk across firms at each time, which is able to capture the nature of changes in default risk ((see the detail discussion in Hovakimian, Kayhan, and Titman (2012)).

with the firm's current risk characteristics or credit quality.

Our empirical evidence strongly supports the rollover risk effect that rollover risk indeed exacerbates default risk, which is consistent with our prediction. In particular we show that one-standard-deviation increase in the change in rollover risk variable lead to a 5.9% increase in default rates. Furthermore, we examine whether being bank dependent magnifies the rollover risk effect. Our results show that the rollover risk effect is more pronounced for bank dependent firms than for public debt dependent firms, which is consistent with our hypothesis.

Next, we consider rollover risk effect could be conditional on credit quality, size, and market economic situation (i.e., during recession or not). We find that rollover risk effect only exist for firms that have poorer credit quality, but not for firms that have good credit quality; size and market economic situation seem not to influence the rollover risk effect in a very different way, of which all firms suffer rollover risk effect. Furthermore, we examine whether being bank dependent magnifies the rollover risk effect across a set of groups as identified by credit quality, size, and recession. We find that the rollover risk effect is significant solely for bank dependent firms, but not for public debt dependent firms in many cases. Our results suggest that poor credit quality, small size, and operating during recession are not necessary of triggering rollover risk effect, and this effect is solely significant for bank dependent firms under these conditions.

This study complements previous literature in several strands. First, our paper contributes to both the literature on debt maturity and the literature on credit risk by providing empirical validation to the theoretical predictions that rollover risk, arising from a firm’s debt maturity structure, increases the firm’s overall credit risk (e.g., He and Xiong (2012), and Morris and Shin (2009)). Unlike most of previous papers which study the rollover risk effect on restricted samples (see e.g., Gopalan et al. (2013)), we provide the most comprehensive empirical evidence on understanding this effect by including all levered firms in the U.S. market.

Second, our paper also complements several recent studies that exploit the global crisis of 2007-2009 to highlight the adverse real impact to firms of not being able to roll over their maturing debt. Almeida et al. (2012) show that firms with a larger proportion of their long-term debt maturing right after August 2007 experienced larger drops in their real investment rates. Duchin, Ozbas, and Sensoy (2010) find that the decline in corporate investment following the global crisis was more pronounced among firms that had more net short-term debt. Our paper differs from these papers in that, whereas these papers examine the effect of rollover risk on firm investments, we examine this effect on firm default risk, and show that rollover risk exacerbates default risk.

Third, Chiu, Peña, and Wang (2014) study the mechanism through which a financial crisis affects the default risk of real-economy levered firms using the natural experiment of the 2007−2009 crisis, and find that firms strongly dependent on bank financing suffer higher increases in default risk, than otherwise similar firms with no dependence on bank financing. Their paper does not explain why bank dependent firm suffer higher default risk during crisis. We provide new evidence showing that rollover risk could be one of explanation to explain why bank dependent higher default risks than public debt dependent firms.

The results presented in this study have important implications for academics and policy makers alike. For academics, the results point out the potential way to improve the current credit risk models is through a better understanding of the interaction between default risk and liquidity risk. Furthermore, it is important to take into account financing sources when assessing the rollover risk and default risk because our results suggest that firm borrowing channel should serve as the critical factor in determining how the rollover risk disproportionally affects the default risk. Finally, the work is important to policy makers, whose objective is to stabilize economic situation, because our results suggests a way to reduce default risk of industrial firms is through regulating firms debt maturity structure.

The remainder of the paper proceeds as follows. The related literature and hypotheses are discussed in Section 2. Section 3 addresses main variables used in this study and data. Section 4 discusses the empirical results, and Section 5 concludes with a discussion of limitations and suggestion for further research.

4.2. Literature Review and Hypothesis Development

In this section, we outline both the theoretical and empirical literature on rollover risk effect on default risk, and discuss how the reliance on bank borrowing affects such effect.

4.2.1. Rollover Risk Effect on Default Risk

This section reviews literatures that theoretically and empirically study rollover risk effect on default risk.

4.2.1.1 Theoretical Background

Recent papers propose theoretical models showing that rollover risk exacerbates default risk. Morris and Shin (2009) incorporate the insights from the bank-run literature[84] into a stylized model to examine the interaction between rollover risk and default risk. They show that a negative fundamental shock can increase the probability of short-term debt holders not rolling over their debt, and thus increase the default probability of a bank. He and Xiong (2012) embed the spirit of Myers (1977) into the Leland and Toft (1996) model, and they show when debt market liquidity deteriorates, firms face rollover losses from issuing new bonds to replace maturing bonds. To avoid default, equity holders need to bear the rollover losses. This intrinsic conflict of interest between debt and equity holders may force equity holders choosing to default at a higher fundamental firm value that the firm would otherwise

[84] See Diamond and Dybvig (1983).

have survived in the absence of rollover risk arising from short-term debt.

The key implication of these theoretical papers is that the amount of a firm's debt maturing in the short term leads to an increase in a firm's overall default probability, aside from traditional default risk factors (such as operating risk and leverage ratio). We regard this increasing causality as the *rollover risk effect* in this study.

Although the above models are built to study default risk due to rollover risk for banks, or for firms that issue corporate bonds, the same logic can be applied to any levered firm. The reason is that once firms have debts, they face refinancing risk.

4.2.1.2. Empirical Evidence

We find some recent empirical evidence in favoring the rollover risk effect. However, empirically examining this effect is still at a very early stage. The only published paper we can find so far is written by Gopalan, Song, and Yerramilli (2013). They find that firms with greater exposure to rollover risk have lower credit quality, where they use the rating information to proxy for default risk. Also, the rollover risk effect is stronger among firms that have speculative grade ratings, declining profitability, and during recessions.

Some unpublished papers also empirically study the rollover risk effect, and they support it. For example, Chen et al. (2012) show that a bigger drop in debt maturity leads to larger increases in credit spreads in the crisis. This maturity effect on credit spreads is more pronounced for firms with high leverage or high systematic risk. Valenzuela (2011) finds an interaction between liquidity and default premiums whereby the debt market illiquidity increases the firms' corporate bond spreads through rollover risk.

Our first hypothesis follows directly from theoretical predictions and empirical evidence that greater exposure to rollover risk increases a firm's overall default probability, and it is,

Hypothesis 1: *Firms with higher exposure to rollover risk should have higher default risk.*

We realized that extant empirical studies only use some particular proxies for default risk, and it make them use the restricted sample that cannot cover all firms. For example, they use credit rating from rating agency, corporate bond spreads, or credit default swap spreads, and their testing samples are limited to large or less-risky firms. We argue that it is important to study to firms that have not been contained so far, and this is especially for unrated firms, which is usually considered as bank dependent firms, because they are represent of almost two-third of firms in the U.S. context. Thus, this paper is to fill this up.

4.2.2. The Impact of Financing Sources on Rollover Risk Effect

This paper aims to fill this up in a way that studying how debt sources drive the effect of rollover risk on default risk.

In this paper, we particularly consider two main debt sources, bank loans and public debts. Based on the degree of relying on either one of debt sources, we discriminate bank dependent (named BD henceforth) firms from public debt dependent (named PDD henceforth) firms. The reason that we focus on the two types of firms is because they are essentially different in many ways, which may disproportionally drive rollover risk effect on credit risk. In particular, as we will illustrate in the below, we expect that BD firms tend to experience higher rollover risk effect than PDD firms.

Carey et al. (1993) show that BD firms are more likely find difficult to borrow long-term debt financing because bank debts have shorter average maturities than public debts. Lemmon and Zender (2007) show that unrated firms tend to have lower debt capacity because they have more volatile cash flows, lower collateral value of assets, and to be more informationally opaque to allow access to arms-length debt. Unrated firms also tend to have higher costs of financial distress. All the above attributes make unrated firms (also known as bank dependent firms) to be potentially more exposed to rollover risk.[85]

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[85] Unrated firms tend to borrow from banks, and make them prone to be bank dependent firms, whereas

Furthermore, Diamond (1991) argues that low credit quality firms that face greater liquidity risk may demand longer-term debt to reduce this risk, but find no lenders willing to supply it at reasonable cost.[86] Mian and Santos (2011) show that only credit-worthy firms are able to choose to refinance at a lower rate when cost of capital rises, whereas credit-poor firms hardly access to new capital at a reasonable cost which incurs substantial rollover losses. In sum, the literature suggests that rollover risk is higher for firm that have lower credit quality firms, and thus for bank dependent firms because they are prone to have lower credit quality compared with public debt dependent firms.

For a firm with high level of rollover risk, it is likely we can find rollover risk effect on default risk for that firm if this effect indeed exists. In contrast, if a firm's rollover risk is slim, there is no way we can find rollover risk on default risk for that firm. So, we expect that BD firms experience larger effect of rollover risk on default risk.

Furthermore, Barclay and Smith (1995) find that overall a firm's debt maturity is negatively correlated with credit risk for unrated firms (i.e., BD firms), while is positively correlated for rated firm (i.e., PDD firms). It indicates that higher short-term debt (i.e., higher rollover risk) could only lead to a higher credit risk specifically for BD firms. Given that BD firms happen to be the firms that with more short-term debts, we expect that BD firm experiences a stronger rollover risk effect on default risk compared with public debt dependent firms. In turn, we hypothesize,

Hypothesis 2: *Rollover risk effect is stronger for bank dependent firms than for public debt dependent firm.*

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firms that have credit rating are often viewed as ones who have access to public debt markets, and thus make them prone to be public debt dependent firms. Many existed literature also use rating information to discriminate bank dependent firms from public debt dependent firms (e.g., Chava and Purnanandam (2011)).

[86] In contrast, higher credit quality firms likely face lower liquidity risk, and can also borrow longer term if liquidity risk concerns do arise.

4.3. Variables and Data

4.3.1. Key Variables

This subsection illustrates the measures we use to proxy for default risk and rollover risk. In our empirical methodology (as shown in the next section), we control for many default risk factors. We also discuss this factor in this section.

4.3.1.1 Measuring Default Risk

The distinctive contribution of this study is to examine rollover risk effects on all levered firms (including rated and unrated firms). Thus, we have limit in using some specific proxies for default risk,[87] and it is necessary to employ default risk measures that are flexible enough to quantify default risk for firms in the entire market.

In this paper, we compute the expected default frequency (EDF) based on Merton model, as the main proxy of default risk, and use Distance-to-Default (DD) as an alternative proxy of default risk for robust.[88] The EDF is widely used as an indicator of default risk for non-financial corporations in the literature (see Bharath and Shumway (2008), Chava and Purnanandam (2010), and Hovakimian, Kayhan, and Titman (2012)).

We compute the EDF and DD measure following well known Moody's KMV approach as:

$$DD = \frac{\log\left(V/B\right) + \left(\mu - \sigma_V^2/2\right)T}{\sigma_V \sqrt{T}} \tag{1}$$

where V is a firm's total asset value, B is a firm's face value of debt, σ_V is the volatility of a firm's asset return, μ is an estimate of the expected long-run return of a firm's asset return, and T is the maturity of a firm's debt. The corresponding implied probability of default, called

[87] For example, we cannot use credit ratings, corporate bond spreads, and credit default swap spreads because they are only applicable for rated firms, for firms that have outstanding issuance of corporate bonds, and for firms issuing credit default swap, respectively.
[88] The analysis on using distance-to-default is provided in Section 4.4.

the expected default frequency (EDF),

$$EDF = N\left(-\left(\frac{\log(V/B)+(\mu-\sigma_V^2/2)T}{\sigma_V\sqrt{T}}\right)\right) = N(-DD) \tag{2}$$

where *N(.)* is the cumulative distribution function for standard normal distribution. EDF measures are statistical predictions of default over some specified time horizon. Here, we calculate one-year default probability. Also we implement one-year window rolling and update it month-by-month, which gives us time-series data of EDF and DD at monthly frequency. The details of the estimation procedure are explained in Appendix A of Chapter 3.

As a measure of default risk, EDF has a number of advantages. Unlike credit ratings, which measure the "relative probability of default" at a fixed number of discrete levels, EDF is a continuous, "absolute" measure of default risk that changes over the course of the credit cycle, reflecting the *changes* in the level of default risk (see the detail discussion in Hovakimian et al. (2012)).[89] Therefore, when the aim is to capture changes in default risk, EDF become as a more suitable measure of default risk at hand, than ratings used in Gopalan et al. (2013).

Furthermore, computing EDF only requires stock price and accounting information, where both are commonly available, and thus it allows us to measure default risks for many firms, rather than a certain group of firms. Thus using EDF leads us to avoid the same sample selection issues.

4.3.1.2. Rollover Risk Variable

In this paper, we follow Gopalan et al. (2013), to exploit ex-ante heterogeneity in firms' long-term debt maturity, and look at the proportion of long-term debt that matures right next year to gauge the impact of the rollover risk. This approach is similar to the one employed in

[89] Hovakimian et al. (2012) mention that ratings reflect "relative" rankings of credit risk at each point in time without reference to an explicit time horizon, which means that although credit ratings provide an ordinal ranking of default risk across firms, depending on the business cycle, the mapping between ratings and short-run default probabilities may change.

Almeida et al. (2012), based on the idea that long-term debt payable during the year depends on the past long-term debt maturity decisions made by the firm, and hence, is less likely to be correlated with the firm's current risk characteristics or credit quality. The rollover risk variable is,

$$\Delta LT-1_{i,t-1} \equiv LT-1_{i,t-1} - LT-1_{i,t-2}, \tag{3}$$

where $LT\text{-}1_{,i,t-1}$ is defined as the amount of the firm *i*'s long-term debt outstanding at the end of year *t-1* that is due for repayment in year *t* (i.e., COMPUSTAT item *dd1* in year *t-1*) scaled by the current book value of total assets. The $\Delta LT\text{-}1_{,i,t-1}$ is the year-on-year change in $LT\text{-}1_{,i,t-1}$. A positive value of $\Delta LT\text{-}1_{,i,t-1}$ implies that firm *i*'s exposure to rollover risk has increased in year *t*.

4.3.1.3. Control Variables

We aim to investigate whether rollover risk serves as an additional default risk factor. In doing so, we control for many relevant firm characteristics that may affect the change in a firm's default risk. They are: (1) *Size* using Log(Total assets), (2) *Leverage* using Total debt/Total assets, (3) *Interest coverage*, (4) *Profitability* using Operating income/Sales, (5) *Tax*, (6) *Market to book* representing growth opportunities, (7) *R&D* expense, (8) Idiosyncratic volatility (denoted as *Idiovol*) representing operating risk, (9) *Tangibility*, and (10) *Cash*. Detailed definitions of all these variables are provided in the Appendix.

The economic rationale behind these variables is presented as follows. (1) *Size* is relevant because larger firms are more diversified, which reduces operating risks, and so they face lower default risk than smaller firms. (2) *Leverage* is included because the higher the leverage, the higher the chance a firm filings for bankruptcy. (3) *Interest coverage* is the ratio used to assess how easily a firm can pay interest on outstanding debt. The lower the ratio, the more the firm is burdened by debt expense, and thus the higher chance the firm cannot survive. (4) *Profitability* is considered because a profitable firm should be less likely to default. (5) *Tax* is negatively associated with default probability as suggested in Hovakimian et el. (2012) that firms with higher tax rates tend to choose capital structures with lower exposure to bankruptcy risk. (6) *Market to book* reflects grow opportunity could have a negative effect on default probability if it represents additional value (over and above book value) that debt holders can in part access in the event of default. (7) *R&D* expenses, which proxy for the firm's brand equity and intellectual capital, respectively, are intangible, and so we also expect them to have a positive effect on default probability. (8) *Idiovol* (i.e., idiosyncratic volatility) implies the probability of a firm's asset value being below the default boundary, so the higher volatility the higher the uncertainty and therefore the higher the default probability. (9) *Tangibility* is expected to have negative effect on default probability because tangible assets lose less of their value in default than do intangible assets. (10) *Cash* reflects a firm's ability to pay its financial debt obligations, so we expect this variable to have negative effect on default probability.

4.3.2. Databases and Descriptive Statistics

We investigate industrial firms in the U.S. market over the period between 1986 and 2011.[90] The financial statement data are from COMPUSTAT, and the stock return data are from the Center for Research Security Prices (CRSP). We lag all accounting information by 6 months because of reporting delay and substitute missing accounting data with the most recent observation prior to it. We exclude financial firms (SIC codes 6000-6999), utilities (SIC codes 4900-4999), and quasi-public firms (SIC codes greater than 8999), whose capital structure decisions can be subject to regulation. In addition, we only select firms with total debt that represents at least 5% of their assets by following Chen et al. (2012). The reason is to avoid contrasting firms that can issue long-term debt versus ones that cannot.

To minimize the effect of these outliers on the results, all variables are winsorized at 1st

[90] We choose 1986 as the initial year is because COMPUSTAT starts to cover credit ratings in 1986.

and 99th percentiles (e.g., values exceeding the 99th percentile are set equal to the 99th percentile). The final sample size is 45,565 firm-year observations, representing 7,272 firms.

To investigate whether bank dependent firms experience more rollover risk effect compared with public debt dependent firms, we first need to identify those borrowers that are likely dependent on their lenders. We use the S&P long-term issuer level rating, extracted from Compustat,[91] to identify a firm as either being bank dependent (i.e., unrated firms) or public debt dependent (i.e. rated firms).

Our sample contains bank dependent firms (in our case, unrated firms) with 27,122 firm-year observations (approximately 60% of the full sample), and public debt dependent firms (in our case, rated firms) with 18,443 firm-year observations (approximately 40% of the full sample).

In Table 12, we present the summary statistics of our main interested variable, *LT-1t-1* (the ratio of long-term debt maturing in one year), our proxies of default risk: the expected default frequency and distance-to-default, and many relevant firm characteristics that are conventionally viewed as important default factors as we illustrate in the previous section. The mean value of EDF are about 0.1, and its median value is 0.001, indicating that the distribution of EDF is highly right-skewed. It also implies almost a half of firms are less likely to default since the median value is very low. The mean (median) for *LT-1t-1* is 0.028 (0.011); an interquartile range of 0.026 implies that there is also wide variation in this short debt maturity measure across firms. In consistent with Gopalan et al. (2013), we focus on Δ*LT-1t-1* in order to take advantage of the sharp variations in *LT-1t-1* over time and across firms.

In Table 12, we also present the firm characteristics that are important for our subsequent analysis. We compare the characteristics of firms that have access to the public debt market

[91] The Compustat data item for credit rating is SPLTICRM, which is defined as the S&P's current opinion of an issuer's overall creditworthiness, apart from its ability to repay individual obligations, and it focuses on the obligor's capacity and willingness to meet its long-term financial commitments.

with the ones that do not have it, by statistically testing the differences of those firm characteristics across BD firms and PDD firms.

Regarding to our main interested variable, *LT-1t-1*, the average level of this variable is 0.035 for BD firms and is only a half of its level with 0.018 for PDD firms. The median value shows a similar pattern whereby it is of 0.018 for BD firms and 0.007 for PDD firms. It indicates that BD firms have more short-term debt, consistent with the finding in Barclay and Smith (1995).

We also find that BD firms tend to be smaller, less profitable, and have lower asset tangibility and lower tax, lower book debt ratios, lower interest coverage, whereas they have higher default risk, higher long-term debts that mature within one year, higher cash holdings, higher market-to-book ratios, higher idiosyncratic volatility, and R&D expenditure. These differences are all statistically significant at 1% level, and generally consistent with expectations (see Chava and Purnanandam, 2011; Hovakimian et al., 2012).[92] The average one-year default probability is about 11% for BD firms and 7% for PDD firms.[93]

[Insert Table 12 Here]

4.3.3. Correlation Matrix

Table 13 contains matrix of Pearson correlation coefficients among the used variables in this paper. These correlations reveal some simple relations among the variables before moving to the regression results. We find that the correlation between *LT-1t-1* and EDF (DD) is 0.19

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[92] Chava and Purnanandam (2011) show that BD firms have lower leverage, lower profitability, whereas they have default risk, market to book, equity volatility. Hovakimian et al. (2012) find a similar result as theirs, and additionally they show that BD firms have lower tangibility and size, whereas they have higher R&D expense. The only difference between our results and theirs is on tax, where they find that tax is lower for BD firms.

[93] Hovakimian et al. (2012) find that the average one-year default probability is about 5% for unrated firms and 1.6% for rated firms. These default probabilities are lower than ours. We consider several reasons. First, our EDF measure is from Merton model, which is the risk neutral default probability, and, this is usually higher than real world default probability. Second, we did not eliminate firms with less than US 1$ million asset or sale. Small firms usually have higher EDF. Third, their sample is between 1985 and 2008, while our sample covers the period of 1986-2011. The last three years in our sample that their sample did not include were rather unstable, so it leads to a larger default probability.

(-0.15) at significance level of 1%. This is consistent with our prediction that the higher the rollover risk the higher the default risk. The correlation between EDF and DD is -0.61. This negative correlation is consistent with notions of both variables to default risk; that is, the higher the EDF the higher the default risk, whereas the lower the DD the higher the default risk. It is worthy to note that the two proxies of default risk are not perfectly correlated, and the correlation is not very high, implying that both proxies are not complemented each other, it is important using both of them in order to provide a more robust analysis.

The correlations between EDF and other default risk factors are also consistent with conventional expectations. That is, *Cash*, *Market to book*, *Tangibility*, *Size*, *Tax*, *Profitability*, and *Interest coverage* are negatively related to default; in contrast, *Idiovol* and *Leverage* are positively related to default. The correlations are totally opposite in the case of DD (expect for *R&D*), which is again consistent with expectations.

[Insert Table 13 Here]

4.4. Empirical Results

The results are presented in five subsections: the first subsections focus on baseline results of testing rollover risk effect on default risk; the second contains the results on testing our hypothesis that whether being bank dependent drives rollover risk effect; the third shows the results on rollover risk effect is conditional on credit quality, size, recession; the fourth presents the results on using distance-to-default as measure of default risk, and the fifth contains the results of various robustness checks.

4.4.1. Baseline Results

We follow Gopalan et al. (2013) by using first difference regression, which can eliminate the firm-specific fixed effects.

$$\Delta Default\ Risk_{i,t} = \alpha + \beta \times \Delta LT{-}1_{i,t-1} + \gamma \times \Delta X_{i,t} + \text{Year FE} \tag{4}$$

The dependent variable, $\Delta Default\ Risk_{i,t}$, represents the change in firm i's default risk in year t against year $t-1$. In this study, the default risk is proxied by the expected default frequency as we have introduced in the previous section. We control the regression for changes (during year t) in many relevant firm characteristics $\left(\Delta X_{i,t} \equiv X_{i,t} - X_{i,t-1}\right)$ that may affect the change in the firm's default risk. They are: (1) *Size* using Log(Total assets), (2) *Leverage* using Total debt/Total assets, (3) *Interest coverage*, (4) *Profitability* using Operating income/Sales, (5) *Tax*, (6) *Market to book* representing growth opportunities, (7) *R&D*, (8) Idiosyncratic volatility (denoted as *Idiovol*) representing operating risk, (9) *Tangibility*, and (10) *Cash*. Detailed definitions of all these variables and economic rationales are provided in Section 3.

We estimate this regression (Eq. (4)) on a panel that has one observation for each firm-year combination, spans the time period 1986-2011. In all the specifications, we also include year fixed effects to control for any macroeconomic variables that may affect changes in firm default risk. The standard errors are robust to heteroscedasticity and are clustered at the industry level, where we define industry at the level of Fama-French 48 industry category.

The baseline results of the estimated default risk equation are reported in Table 14. The variable of particular interest to our study is $\Delta LT\text{-}1_{,i,t-1}$, the change in long-term debt that matures in a year. Column 1 reports the estimators without including control variables. In the case of using EDF as dependent variable, the results show that the estimated coefficient of $\Delta LT\text{-}1_{,i,t-1}$ is positive and significantly different from zero at the 1% level. This is consistent with our hypothesis 1. The estimated coefficient along with $\Delta LTi,t\text{-}1$ is 0.067, which implies that a one-standard-deviation increase in the $\Delta LTi,t\text{-}1$ will lead to a 0.0062 increase in EDF.[94] Given a mean EDF of 0.105, the result indicates a 5.9% increase in default rates. Thus, the

[94] Using the full sample, the mean and the standard deviation of $\Delta LTi,t\text{-}1$ are 0.002 and 0.09 respectively. We rely on this information to quantify the economic impact of rollover risk effect. We sum the mean value of $\Delta LTi,t\text{-}1$ and the standard deviation of $\Delta LTi,t\text{-}1$ to represent a one-standard deviation increase in $\Delta LTi,t\text{-}1$. Then, the economic impact is computed as follows. We multiply the above summation and the estimated coefficient of $\Delta LTi,t\text{-}1$, and then divide it by the unconditional mean value of EDF or DD.

effect of rollover risk on default risk is not only statistically significant but also economically significant.

After controlling for other default risk factors (see Column 2), we find that the estimated coefficient of $\Delta LTi,t\text{-}1$ remains its statistical significance at 1% level. As for influence of control variables on EDF, the results are basically consistent with conventional expectations. In that, we find *Cash*, *Market to book*, *Tax*, *Profitability*, and *Interest coverage* are significantly negatively related to EDF, whereas *Idiosyncratic risk* and *leverage* are significantly positively related to EDF. However, some variables do not seem to be strong default risk factors in our case; they are *Tangibility*, *Size*, and *R&D*.

[Insert Table 14 Here]

4.4.2. Rollover Risk Effect Dependent on Financing Sources

We hypothesize that bank dependent firms likely experience larger effect of rollover risk on default risk (see Hypothesis 2). This paper aims to provide empirical evidence in supportive of this hypothesis.

In doing so, we create zero-one dummy variable, where it equals to one if the firm is identified as a BD firm, otherwise 0. We call it *BD_dummy*. Furthermore, we create two separate interaction terms, where one of them is between a measure of rollover risk factor (i.e., $\Delta LTi,t\text{-}1$) and dummy variable of being BD firms, and the other one is between a measure of rollover risk factor (i.e., $\Delta LTi,t\text{-}1$) and dummy variable of not being BD firms, which is (*1-BD_dummy*) because non-BD firms are identified as PDD in this study. The two interactions make the effect of rollover risk on default risk conditional on the dependence of firm's financing source, and thus allow a test of the hypothesis that bank dependence strengthens the effect of rollover risk on default risk. The testing methodology used for this issue is based on our Equation (4) by replacing of $\Delta LT\text{-}1_{,i,t-1}$ with the two interaction terms, displayed as follows,

$$
\begin{aligned}
\Delta Default\ Risk_{i,t} = \alpha &+ \beta_1 \times \Delta LT-1_{i,t-1} \times BD\_dummy \\
&+ \beta_2 \times \Delta LT-1_{i,t-1} \times \left(1 - BD\_dummy\right) \\
&+ \gamma \times \Delta X_{i,t} + \text{Year FE}
\end{aligned} \tag{5}
$$

If being bank dependence strengthens the effect of rollover risk on default risk, then the coefficient of the variable of $\Delta LTi,t\text{-}1 \ x\ BD\_dummy$, "$\beta_1$" should have a positive and statistically significant coefficient on the regression. On the other hand, if PDD firm experience lower effect of rollover risk on default risk, the interaction variable of $\Delta LTi,t\text{-}1\ x\ (1\text{-}BD\_dummy)$, "$\beta_2$" would be non-significant, or significant but less important than β_1.

We notice that the distributions of $\Delta LT\text{-}1_{,i,t-1}$ are very different between BD and PDD firms; in that, the mean of $\Delta LT\text{-}1_{,i,t-1}$ is 0.0026 for BD and 0.0013 for PDD, and the standard deviation is 0.112 for BD and 0.042 for PDD. Thus, rather than comparing the estimated coefficients directly, we compute their economic impacts by using their respective means and standard deviations on BD and PDD firms. In the following, we assess whether being bank-dependent drives the effect rollover risk effect by comparing economic impacts along with these two interaction variables.

Column 3 and 4 of Table 14 show the results on running regression of Eq. (5). In Column 3, we find that the estimated coefficient of $\Delta LTi,t\text{-}1x\ BD\_dummy$ is significant, while not significant for $\Delta LTi,t\text{-}1x\ (1\text{-}BD\_dummy)$, though they both have positive sign. It indicates that firms experience a growth in their long-term debts maturing the coming year experience higher default rates, and this effect is stronger for BD firms, and seems weak for PDD firm. This is consistent with our hypothesis 2. In particular, a one-standard-deviation increase in the $\Delta LTi,t\text{-}1$ will lead to a 0.0076 increase in EDF. Given a mean EDF of 0.124, the result indicates that a one-standard deviation increase in *LT-1t-1* leads to a 6.1% increase in default rates. After controlling for other default risk factors, the rollover risk effect still holds; in that, for BD firms and is significant at 1% level. The rollover risk effect seems become a little bit stronger for PDD firms, where the estimated coefficient of $\Delta LTi,t\text{-}1x\ (1\text{-}BD\_dummy)$ is now significant at 10% level.

Overall, our results suggest that the rollover risk effect is more pronounced for BD firms, which is again consistent with our hypothesis 2, even accounting for many relevant default risk factors. We consider that the above results merely provide low boundary of the effect of rollover risk on credit risk, because short-term debt (less one year maturity debts) also likely amplify this effect, and this is especially so in the case of BD firms because BD firms use more short-term debts compared with PDD firms.[95]

4.4.3. Rollover Risk Effect Conditional on Credit Quality, Size, and Recession

We consider rollover risk effect could be amplified through other factors as suggested in literature. In particular, we consider credit quality, size, and market economic situation (undergoing recession or not).[96] We discuss the rationale of why choosing these factors in the following.

First, we expect that the rollover risk effect on credit risk should be stronger for poor credit quality firms. The reason is that, poor-credit quality firms likely find it more difficult to lengthen maturity. Also, Diamond (1991) argues that low credit quality firms that face greater liquidity risk may demand longer-term debt to reduce this risk, but find no lenders willing to supply it at reasonable cost. Mian and Santos (2011) show that only credit-worthy firms are able to choose to refinance at a lower rate when cost of capital rises, whereas credit-poor firms less likely access to new capital at a reasonable cost which incurs substantial rollover losses.

Second, as for size, on the one hand, large firms are more diversified and have longer-term debt structure. Small firms have more cash reserves and lower debts. All these attributions can reduce the rollover risk effect. On the other hand, large firms rely more on

[95] The reason that we do not use short-term debt is because of the potential endogenous problem that short-term debt is highly related to default risk as highlighted in the literature.
[96] Recession identifies the years classified by the NBER as recessionary. Those years are 1990, 1991, 2001, 2002, 2008, and 2009.

debt financing, and small firms may face more problems in refinancing especially when debt market is in crunch. Taken together, we expect that rollover risk effect may be dependent on firm size. However there is no clear prediction on how size influences rollover risk effect, and we consider it as an empirical question.

Third, He and Xiong's (2012) theoretical model demonstrates that debt market friction is the key trigger to cause rollover risk effect. During recession, it is often to observe debt market friction. Also, Gopalan et al. (2013) provide empirical evidence showing that rollover risk effect exists both during recession and no recession periods, and especially so in the case of recession. Thus we expect that rollover risk effect exists all the time and may be stronger during weak economic times.

To test whether rollover risk is driven by credit quality, we split the sample into two halves based on the sample median value of EDF, of which the high-EDF group is considered as bad credit quality group, whereas the low-EDF group is viewed as good credit quality group. We implement the baseline regression (Eq. (4)) on the two groups separately. The results are reported in Panel A of Table 15. We find that firms in the group that has poorer credit quality experience higher rollover risk effect because we find the estimated coefficient of $\Delta LT_{i,t-1}$ is only significantly positive at 1% level for bad-credit-quality group, but not for good-credit-quality group (see Column 1 and 2). This may imply that there are some unobservable variables that discriminate BD and PDD besides credit quality, because we find that even among credit-worse firms BD firms exposures higher rollover risk effect.

To test whether size drives the rollover risk effect, similarly, we split the whole sample into two halves based on the sample median value of size: large-size group versus small-size group. Our results seem to indicate firms suffer rollover risk effect in a very significant way, irrespective of the scale of firms, because we find that the estimated coefficient of $\Delta LT_{i,t-1}$ in two model specifications under item "Size" are positive and significant at 1% level (see

Column 3 and 4 of Panel A).

As for testing the influence of market economic situation, we implement baseline regression for the subsample that covers recession years and the subsample that does not. We find that rollover risk effect exist, irrespective of undergoing recession, because the estimated coefficient of $\Delta LTi,t\text{-}1$ in all model specifications under item "Recession" are positive and significant at 1% level. Because we find that rollover risk effect exists, both during recession, and non recession, this finding suggests that the root of rollover risk is firm fundamental factors rather than credit market conditions.

[Insert Table 15 Here]

We further examine whether the results we unveiled in the above is driven by being bank dependent firm or not. In doing so, we re-examine Panel A of Table 15 with alternative regression specification (Eq. (5)). The results are reported in Panel B of Table 15. We find financing sources indeed have impacts on the rollover risk effect in many cases.

First, within the group that has bad credit quality (Column 2 of Panel B), the estimated coefficient of $\Delta LTi,t\text{-}1$ is highly significant (at 1% level) for BD firms, but shows weak significance (10% level) for PDD firms. Second, within the group that has small size, the estimated coefficient of $\Delta LTi,t\text{-}1$ is only significant for BD firms, but not for PDD firms. Third, either during recession or not, the estimated coefficient of $\Delta LTi,t\text{-}1$ is only significant at 5% level (or better) only for BD firms, but not for PDD firms.

Overall, our results suggest that rollover risk effect is dependent on being bank dependent firms or not. In particular, such effect is amplified solely for BD firms with poor credit quality, have small size, and operate during recession.

4.4.4. Alternative Default Risk Measure: Distance-to-Default

By construction, EDF is a non-linear function of DD (see the detail in Section 2.1.), and thus they are not perfectly correlated. For robustness, we use an alternative popular measure of DD to see whether our hypotheses still hold. The DD is widely applied in literature as a measure of default risk (see e.g., Goyal and Wang (2013)). The DD is the number of standard deviations that a firm's asset value is away from its default threshold at the forecasting horizon. Therefore it is inversely related to default risk and EDF measure as well.

We replace EDF with DD and re-examine all regression specifications in Table 14 and Table 15. The results are reported in Table 16 and 17. In contrast to the case of using EDF as proxy of default risk, a negative estimated coefficient of $\Delta LTi,t\text{-}1$ indicates that there is rollover risk effect on default risk. Generally speaking, the results are consistent with the results of using EDF as proxy of default risk, and comply with our Hypothesis 1. In particular, we find that the estimated coefficient of $\Delta LTi,t\text{-}1$ is significantly negative at 5% level (or better), irrespective of including control variables or not (see Column 1 and 2 of Table 16). Also, control variables influence DD with their expected directions. We find that *Cash*, *Market to book*, *Size*, *Tax*, *Profitability*, and *Interest coverage* are significantly positively related to DD, and *Idiosyncratic risk*, *R&D*, and *Leverage* are significantly negatively related to DD. However, *Tangibility* does not seem to be strong default risk factor in our case.

[Insert Table 16 Here]

Column 3 and 4 o Table 16 show the results on running regression of Eq. (5) with DD as the dependent variable. In the regression without including control variables (Column 3), the coefficient of $\Delta LTi,t\text{-}1$ is negatively significant at 5% level for BD firms, but it is weak significance for PDD firms, of which the coefficient of $\Delta LTi,t\text{-}1$ is only significant at 10% level. After controlling for other default risk factors, the result still holds (see Column 4), where the $\Delta LTi,t\text{-}1$ is significant at 1% level for BD firms, while 5% for PDD firms. Overall, this result is consistent with the result of using EDF as proxy of default risk, and consequently consistent with the Hypothesis 2.

We also re-examine whether the rollover risk effect is conditional on credit quality, size, and market economic situation as we discussed in Section 4.3 by using DD as the proxy of default risk. The results are reported in Table 17. In almost all of cases, the results are consistent with the analysis as we provided in Section 4.3; that is rollover risk effect is dependent on being bank dependent firms or not. In particular, such effect is amplified solely for BD firms with poor credit quality, have small size, and operate during recession.[97]

[Insert Table 17 Here]

4.4.5. Robustness Tests

We conduct a battery of robustness checks. First, we use credit rating provided by rating agency as a proxy for default risk. Second, we use an alternative methodology in testing the influence of credit quality, size, and recession. Third, we sort firms based on terciles and quartiles, instead of medians as we used in the main analysis.

4.4.5.1. Using Credit Rating

Following Gopalan et al. (2013), we use credit rating provided in rating agency as the proxy of default risk. The letter ratings are transformed into numerical equivalents, using an ordinal scale that ranges from 1 for the highest-rated firms (AAA) to 22 for the lowest-rated firms (D: Default). Note that the EDF (or DD) measure of default probability is available for all sample observations, whereas only 11,110 of the sample observations are for firms with credit ratings.

We re-do the baseline regression (Eq.(4)), and the results are reported in Table 18. We find our Hypothesis 1 still holds, and is also consistent with the result of Gopalan et al. (2013).

[Insert Table 18 Here]

4.4.5.2. Dummy Variables on Credit Quality, Size, and Recession

We use an alternative methodology in test the influence of credit quality, size, and

[97] We find only one exception that upon poor credit quality group, the rollover risk effect is indifferently significant between BD firms and PDD firms (See Column 2, Panel B of Table 17).

recession. That is, rather than dividing the entire sample into two groups, we create zero-one dummy variables on credit quality, size, and recession, and their interaction terms with rollover risk variable, and put them into our baseline regression one time-by-one time. We run regression on the entire sample with the new regression, and we find the results are still consistent with the main results. The results are reported in Table 19.

[Insert Table 19 Here]

4.4.5.3. Alternative Identification on Separating Firms

Unlike the main analysis of which using sample median value to identify firms' type, we sort firms into terciles based on their credit qualities and size. When using EDF (DD) as proxy for default, firms included in the first tercile as those with good (bad) credit quality and small size, and firms included in the third tercile as those with bad (good) credit quality and large size. We also change terciles into quartiles, and re-do all model specifications in Table 15 and 16 again. The results are reported in 20 to 23, and they are consistent with the arguments as we provided in the above based on using sample median.

[Insert Table 20 Here]

[Insert Table 21 Here]

[Insert Table 22 Here]

[Insert Table 23 Here]

4.5. Conclusion

We empirically examine the effect of rollover risk on default risk, and whether firm financing source drives this effect in the U.S. context over the period between 1986 and 2011.

Recent theoretical literature argues that rollover risk could serve as an additional source of credit risk, because it exacerbates default risk. We refer to as *rollover risk effect*. From empirical viewpoint, extant studies only unveil some parts of this rollover risk effect due to limitation of the sample they used. Their samples are restricted to firms that have credit ratings, bond spreads, or credit default swap spreads. To our best understanding, we provide the most comprehensive empirical study of understanding this rollover risk effect.

Furthermore, we provide new empirical evidence on studying to what extent that financing sources drive the effect of rollover risk on default risk. Our results strongly suggest that being bank dependent magnifies the rollover risk effect. Furthermore, our results suggest that poor credit quality, small size, and operating during recession are not necessary of triggering rollover risk effect, and this effect is solely significant for bank dependent firms under these conditions.

Gopalan et al. (2013) point out that "bond market investors seem to recognize the effect of rollover risk because bonds issued by firms with a larger amount of long-term debt (scaled by assets) payable within a year trade at higher yield spreads." In this study, we only consider the rollover risk effect on a firm's overall default probability. A worthwhile avenue for further research is to investigate whether banks recognize the rollover risk effect by charging different bank loan spreads among firms with heterogeneous rollover risk.

Appendixes

Variable Definitions

- *Cash* is the ratio of book value of cash and marketable securities (Compustat item che) to the book value of total assets (Compustat item at).
- *Idiovol* (Idiosyncratic volatility) is the standard deviation of daily excess returns relative to the CRSP value-weighted index for each firm's equity during a year.
- *Interest coverage* is the ratio of operating income after depreciation (Compustat items oiadp+ xint) to the total interest expenditure (Compustat item xint).
- *Leverage*: Total debt/Total assets is the ratio of total debt (Compustat items dlc + dltt) to the total assets
- *Market to book* is the ratio of market value of total assets to the book value of total assets. We calculate the market value of total assets as the sum of book value of total assets and the market value of equity less the book value of equity.
- *Profitability* is the ratio of operating income after depreciation (Compustat item oiadp) to total sales (Compustat item sale).
- *R&D* is the ratio of research and development expenditure (Compustat item xrd) to book value of total assets (Compustat item at). We replace missing values of xrd as zero.
- *Size* is the natural logarithm of the book value of total assets (Compustat item at).
- *Tangibility* is the ratio of book value of property plant and equipment (Compustat item ppent) to the book value of total assets (Compustat item at).
- *Tax* is the ratio of tax expenditure (Compustat item txt) to book value of total assets (Compustat item at).

CHAPTER 5

Final Remarks

The 2007–2012 crisis highlights that understanding systemic risk is important to find a way of stabilizing the whole financial system. We contribute to this issue by proposing a new measure of quantifying systemic risk of which we include two crucial factors: common factor exposure and tail risk dependence. Furthermore, we examine the impact of the alternative financing sources (banks, debt markets) on the default risks of non-financial firms listed in the U.S. stock market during the crisis of 2007−2010. The results suggest that bank dependent firms experienced high default risk, which is consistent with bank supply shock theory. Finally we examine whether rollover risk exacerbates default risk, and whether financing sources drive this effect. We suggest that financing sources indeed drive this effect, and in particular our results strongly suggest that being bank dependent magnifies this effect.

As a closing remark, there are still many questions that need to be uncovered beyond of the findings in this thesis. In particular, to what extent that financial markets affects real economy sectors in terms of firm default risk still largely unanswered, and we merely shed light on some parts of this issue in this work.

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Table 1. Summary statistics.

This table reports summary statistics for several risk measures for each sector of the financial industry, from December 1996 to December 2011, for a total of 181 monthly observations. *SIZE* (in millions) is the logarithm of aggregated total assets for the ten biggest firms in each sector. The *LVG* is the quasi-market value of assets divided by the market value of equity, with weighted averages based on the values of market equity. The *RET* is annual returns. *DD*, *NoD*, and *PIR* (scaled by multiplying them by 10^6) are systemic risk measures. The subindex "ben" identifies measures computed from the benchmark model (without correlated jump terms).

Sector	Statistics	*SIZE*	*LVG*	*RET*	*DD*	*NoD*	*PIR*	DD_{ben}	NoD_{ben}	PIR_{ben}
Depositories	Min	14.380	4.890	-0.530	-0.240	0.000	0.000	1.120	0.000	0.000
	Max	15.800	34.040	1.760	16.230	8.030	69.255	16.730	3.860	9.475
	Mean	15.140	7.940	0.090	6.310	0.790	4.503	8.000	0.260	0.343
	Median	15.070	6.910	0.070	5.900	0.010	0.020	7.430	0.000	0.000
	Std	0.440	3.400	0.260	3.930	1.720	11.765	4.030	0.650	1.123
Broker-Dealers	Min	13.760	6.240	-0.540	-0.660	0.000	0.005	0.020	0.000	0.000
	Max	15.350	40.050	1.380	8.440	6.110	208.445	16.700	5.250	29.956
	Mean	14.540	12.260	0.210	2.590	2.260	22.221	6.010	0.960	2.614
	Median	14.470	10.960	0.160	1.980	2.140	6.334	5.140	0.790	0.693
	Std	0.390	4.800	0.390	2.110	1.820	39.363	3.800	1.060	4.785
Insurance	Min	13.450	4.140	-0.540	0.910	0.000	0.000	0.390	0.000	0.000
	Max	15.020	82.960	2.200	21.230	5.390	41.335	26.290	3.220	22.541
	Mean	14.460	11.930	0.120	10.990	0.360	3.757	12.180	0.230	1.421
	Median	14.600	7.620	0.120	10.870	0.000	0.000	11.880	0.000	0.000
	Std	0.470	14.160	0.340	4.570	1.010	10.084	5.380	0.580	4.281
Others	Min	13.450	4.310	-0.670	-0.780	0.000	0.001	-1.970	0.000	0.000
	Max	15.390	173.300	1.900	7.390	8.900	288.020	11.260	6.770	211.190
	Mean	14.810	11.220	0.110	3.450	2.380	39.902	5.510	1.420	15.074
	Median	14.890	7.690	0.110	3.750	1.450	3.699	6.040	1.000	0.919
	Std	0.490	16.920	0.340	2.170	2.400	78.679	3.150	1.730	39.273

Table 2. Estimation results: correlated jumps.

This table presents the average values of λ, *mu_coj*, and *std_coj* for the pre-crisis, crisis, and post-crisis periods in Column 1, 3, 5, respectively. The pre-crisis period runs from July 2005 to June 2007, the crisis period from July 2007 to June 2009, and the post-crisis period is from July 2009 to June 2011. Each period consists of 24 observations. Columns 2 and 4 report the results of the independent samples t-test, for which the null hypothesis is that the means of the two groups are equal. For each parameter, Column 2 (4) reports the difference in the average values for crisis and pre-crisis (post-crisis) periods, with the *p*-values in brackets. Panel A refers to depositories, Panel B to broker-dealers, Panel C to insurance companies, and Panel D to others sectors.

	Pre-Crisis (1)	Crisis versus Pre-Crisis (2)	Crisis (3)	Crisis versus Post-Crisis (4)	Post-Crisis (5)
Panel A: Depositories					
λ	0.0394	0.0964 ***	0.1358	0.0828 ***	0.0530
		(<0.0001)		(0.0015)	
mu_coj	0.0049	-0.0135 ***	-0.0086	-0.0078 *	-0.0008
		(0.0007)		(0.1039)	
std_coj	0.0178	0.0653 ***	0.0831	0.0128	0.0702
		(<0.0001)		(0.3478)	
Panel B: Broker-Dealers					
λ	0.0347	0.0258 **	0.0606	0.0074	0.0532
		(0.0244)		(0.5427)	
mu_coj	0.0030	-0.0162 **	-0.0132	-0.0101	-0.0031
		(0.0476)		(0.2235)	
std_coj	0.0318	0.0535 ***	0.0853	0.0256 ***	0.0597
		(<0.0001)		(0.0054)	
Panel C: Insurance Companies					
λ	0.0713	0.0561 ***	0.1274	0.0626 ***	0.0648
		(0.0030)		(0.0011)	
mu_coj	0.0013	-0.0041 ***	-0.0028	-0.0024 **	-0.0004
		(<0.0001)		(0.0177)	
std_coj	0.0206	0.0634 ***	0.0840	-0.0002	0.0842
		(<0.0001)		(0.9896)	
Panel C: Others					
λ	0.1003	0.0963 ***	0.1967	0.1026 ***	0.0941
		(0.0015)		(0.0031)	
mu_coj	-0.0008	-0.0222 **	-0.0230	-0.0234 **	0.0004
		(0.0187)		(0.0160)	
std_coj	0.0273	0.1029 ***	0.1302	0.0483 ***	0.0820
		(<0.0001)		(0.0081)	

Table 3. Estimation results: structural-form parameters.

This table reports the average values of the estimated parameters from our structural-form model and the benchmark model (notated "ben"). The sample period spans December 1996 to December 2011, with 181 observations. The reported numbers in μ, $\mu_{\_ben}$, ξ, and $\xi_{\_ben}$ are 10,000 times the raw values. The "diff." indicates stands for the testing results of independent samples t-tests, for which the null hypothesis is that the means of the two groups are equal for each pair of parameters. Columns 3, 6, and 9 report the differences of the average values of the estimated parameters, along with *p*-values in brackets.

Sector	μ (1)	$\mu_{\_ben}$ (2)	*diff.* (3)	δ (4)	$\delta_{\_ben}$ (5)	*diff.* (6)	ξ (7)	$\xi_{\_ben}$ (8)	*diff.* (9)
Depositories	0.9996	0.9247	0.0749	0.4486	0.5193	-0.0707 ***	0.2714	0.4960	-0.2246 ***
			(0.8814)			(<0.0001)			(<0.0001)
Broker-Dealers	2.8938	3.1188	-0.2250	0.5945	0.6326	-0.0381 ***	0.5957	1.0429	-0.4472 ***
			(0.6611)			(0.0012)			(<0.0001)
Insurance Companies	-0.9960	-0.1626	-0.8334	0.7224	0.7842	-0.0618 ***	0.5299	1.5100	-0.9800 ***
			(0.2683)			(0.0003)			(<0.0001)
Others	2.7060	3.2008	-0.4948	0.3534	0.4157	-0.0622 ***	0.1897	0.8126	-0.6229 ***
			(0.2911)			(<0.0001)			(<0.0001)

Table 4. Granger causality tests, 1996–2011.

This table reports the results of Granger causality tests for full-model (FM) systemic risk indicators compared with benchmark-based ones and with the public financial stress index STLFSI. The sample contains 181 monthly observations from December 1996 to December 2011. Panel A refers to levels and Panel B includes the results for first differences. The tests for each risk indicator apply across industries. Columns 1 and 2 (3 and 4) indicate if the systemic risk indicators Granger cause the benchmark-based measures (STLFSI), and their reverse direction. The Granger causality tests' lag-lengths are selected according to the Schwarz criterion; heteroskedastic and correlated errors corrected. For each test, the *p*-values appear in brackets, and the lag-length of VAR is reported for statistically significant cases.

***, **, and * are significant at 1%, 5%, and 10% levels, respectively.

		FM leads Benchmark (1)		Benchmark leads FM (2)		FM leads STLFSI (3)		STLFSI leads FM (4)	
Measure	Sector	*P*-value		*P*-value		*P*-value		*P*-value	
Panel A: levels									
DD	Depositories	(0.009)***	lag(1)	(0.695)		(0.015)**	lag(1)	(0.105)	
	Broker-Dealers	(0.001)***	lag(1)	(0.305)		(0.001)***	lag(1)	(0.588)	
	Insurance Com.	(0.005)***	lag(1)	(0.502)		(0.046)**	lag(2)	(0.015)**	lag(2)
	Others	(0.000)***	lag(1)	(0.218)		(0.094)*	lag(1)	(0.016)**	lag(1)
NoD	Depositories	(0.001)***	lag(6)	(0.000)***	lag(6)	(0.912)		(0.005)***	lag(1)
	Broker-Dealers	(0.009)***	lag(1)	(0.547)		(0.026)**	lag(2)	(0.986)	
	Insurance Com.	(0.000)***	lag(5)	(0.188)		(0.014)**	lag(2)	(0.039)**	lag(2)
	Others	(0.000)***	lag(1)	(0.111)		(0.146)		(0.943)	
PIR	Depositories	(0.047)**	lag(2)	(0.802)		(0.249)		(0.001)***	lag(2)
	Broker-Dealers	(0.000)***	lag(1)	(0.216)		(0.366)		(0.325)	
	Insurance Com.	(0.000)***	lag(2)	(0.063)*	lag(2)	(0.017)**	lag(2)	(0.104)	
	Others	(0.000)***	lag(1)	(0.249)		(0.718)		(0.167)	
Panel B: first differences									
DD	Depositories	(0.014)**	lag(1)	(0.342)		(0.450)		(0.017)**	lag(1)
	Broker-Dealers	(0.013)**	lag(2)	(0.119)		(0.006)***	lag(1)	(0.909)	
	Insurance Com.	(0.529)		(0.590)		(0.024)**	lag(1)	(0.211)	
	Others	(0.002)***	lag(2)	(0.199)		(0.798)		(0.177)	
NoD	Depositories	(0.045)**	lag(2)	(0.000)***	lag(2)	(0.501)		(0.443)	
	Broker-Dealers	(0.034)**	lag(1)	(0.696)		(0.009)***	lag(1)	(0.943)	
	Insurance Com.	(0.000)***	lag(4)	(0.088)*	lag(4)	(0.017)**	lag(4)	(0.117)	
	Others	(0.050)**	lag(1)	(0.852)		(0.880)		(0.922)	
PIR	Depositories	(0.025)**	lag(1)	(0.776)		(0.378)		(0.025)**	lag(1)
	Broker-Dealers	(0.000)***	lag(2)	(0.289)		(0.239)		(0.344)	
	Insurance Com.	(0.109)		(0.115)		(0.009)***	lag(1)	(0.511)	
	Others	(0.021)**	lag(3)	(0.405)		(0.736)		(0.441)	

Table 5. Predictive power.

This table presents the results in comparing predictive ability for STLFSI, we first run a regression, in which the explanatory variables are the lagged terms of STLFSI and of the benchmark, as shown in Equation (25). Next we include the lagged terms of the full model to check for its incremental predictive ability, as shown in Equation (26). With an *F-test* (Equation (27)), we examine if the difference in R^2 values across the two regressions differs significantly from 0. Bold font reveals cases where R^2 is higher in Equation (26) than in Equation (25).

***, **, and * are significant at 1%, 5%, and 10% levels, respectively.

		R^2 Eq. (25)	R^2 Eq. (26)	*F-statistics*	*P-value*
Panel A: levels					
DD	Depositories	0.917	**0.921**	7.761 ***	0.006
	Broker-Dealers	0.918	**0.919**	0.855	0.358
	Insurance Companies	0.917	**0.921**	4.800 ***	0.009
	Others	0.918	0.918	0.991	0.321
NoD	Depositories	0.922	**0.923**	1.963	0.163
	Broker-Dealers	0.918	0.918	0.401	0.527
	Insurance Companies	0.938	0.938	0.998	0.319
	Others	0.917	**0.920**	6.755 **	0.010
PIR	Depositories	0.917	0.917	0.000	1.000
	Broker-Dealers	0.918	**0.920**	5.225 **	0.024
	Insurance Companies	0.919	**0.923**	9.125 ***	0.003
	Others	0.917	**0.918**	2.227	0.137
Panel B: first differences					
DD	Depositories	0.060	**0.063**	0.530	0.467
	Broker-Dealers	0.071	**0.078**	1.344	0.248
	Insurance Companies	0.068	**0.102**	6.494 **	0.012
	Others	0.063	0.063	0.007	0.931
NoD	Depositories	0.083	**0.110**	5.281 **	0.023
	Broker-Dealers	0.070	**0.092**	4.176 **	0.043
	Insurance Companies	0.307	**0.312**	1.303	0.255
	Others	0.062	0.062	0.010	0.922
PIR	Depositories	0.069	**0.072**	0.680	0.411
	Broker-Dealers	0.060	**0.113**	10.453 ***	0.002
	Insurance Companies	0.063	**0.336**	71.949 ***	0.000
	Others	0.061	**0.065**	0.705	0.402

Table 6. DD Descriptive statistics and preliminary test.

The table shows descriptive statistics and preliminary tests on distance-to-default measures before and during the crisis for subgroups of firms formed in the second quarter of 2006. The sample consists of 113,409 firm-month observations from the third quarter of 2006 through the first quarter of 2010. The crisis period is divided into five time phases: (1) pre-crisis (2006Q3−2007Q2); (2) first year crisis (2007Q3−2008Q2); (3) pre-Lehman (2008Q3); (4) post-Lehman (2008Q4−2009Q1); (5) last year crisis (2009Q2−2010Q1). Moreover the sample of firms is separated into six subgroups for testing BSST, CSST, DST, and the substitution effect. Firms that have records in DealScan LPC database and/or have ratings are identified as credit-dependent firms (CDF), while those that have not are classified as non-credit-dependent firms (NCDF). Within the CDF group, firms are further divided into five subsets based on the intensity of bank relationships and whether the firm is rated or unrated. They are denoted as (1) SBPD when the subgroup contains rated firms with strong bank relationship; (2) SB when the subgroup contains unrated firms with strong bank relationship; (3) WBPD when the subgroup contains rated firms with weak bank relationship; (4) WB when the subgroup contains unrated firms with weak bank relationship; (5) PDD when the subgroup contains rated firms without bank relationship. P-values are reported by using Wilcoxon one-way sample t-test. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	NCDF	CDF	SBPD	SB	WBPD	WB	PDD
			{strong bank dependent firms}		{weak bank dependent firms}		
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1. Pre-crisis (2006Q3-2007Q2)	7.7766	8.2220	9.1201	8.3988	7.8201	8.3615	5.6502
2. First year (2007Q3-2008Q2)	6.6528	6.8656	7.4590	6.4818	6.3118	7.2029	5.3560
3. Post-Lehman (2008Q4-2009Q1)	1.9855	1.7805	1.8172	1.8640	1.3239	2.0097	1.3474
4. Last year (2009Q2-2010Q1)	3.9130	3.9096	4.0032	3.8704	3.6674	4.1126	3.3095
Diff 2-1	-1.1238 ***	-1.3564 ***	-1.6611 ***	-1.9170 ***	-1.5083 ***	-1.1586 ***	-0.2942
P-value	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.3131)
%Diff 2-1	-14.45	-16.50	-18.21	-22.82	-19.29	-13.86	-5.21
Diff 4-1	-3.8637 ***	-4.3124 ***	-5.1169 ***	-4.5284 ***	-4.1527 ***	-4.2489 ***	-2.3407 ***
P-value	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
% Diff 4-1	-49.68	-52.45	-56.10	-53.91	-53.10	-50.81	-41.42
Post-Lehman versus pre-Lehman							
2009Q1	1.8284	1.5048	1.5111	1.6053	1.1093	1.7302	1.0831
2008Q4	2.0755	2.0247	2.1031	2.1124	1.5529	2.2413	1.5240
2008Q3 (pre-Lehman)	4.2534	4.6000	4.9394	4.3888	4.2388	4.7537	3.7979
Diff 2009Q1-2008Q3	-2.4250 ***	-3.0952 ***	-3.4283 ***	-2.7835 ***	-3.1295 ***	-3.0235 ***	-2.7148 ***
P-value 2008Q3 = 2009Q1	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
%Diff 2009Q1-2008Q3	-57.01	-67.28	-69.40	-63.42	-73.82	-63.60	-71.48

Table 7. Analysis of default risk indicators.

The table shows the cross-sectional variations of time-series changes in distance-to-default before and during the crisis for subgroups of firms formed in the second quarter of 2006. The crisis period is divided into five time phases: (1) pre-crisis (2006Q3−2007Q2); (2) first year crisis (2007Q3−2008Q2); (3) pre-Lehman (2008Q3); (4) post-Lehman (2008Q4−2009Q1); (5) last year crisis (2009Q2−2010Q1). Moreover the sample of firms is separated into six subgroups for testing BSST, CSST, DST, and the substitution effect. Firms that have records in DealScan LPC database and/or have ratings are identified as credit-dependent firms (CDF), while those that have not are classified as non-credit-dependent firms (NCDF). Within the CDF group, firms are further divided into five subsets based on the intensity of bank relationships and whether the firm is rated or unrated. They are denoted as (1) SBPD when the subgroup contains rated firms with strong bank relationship; (2) SB when the subgroup contains unrated firms with strong bank relationship; (3) WBPD when the subgroup contains rated firms with weak bank relationship; (4) WB when the subgroup contains unrated firms with weak bank relationship; (5) PDD when the subgroup contains rated firms without bank relationship. The "Time-series changes" in distance-to-default is computed by subtracting its pre-crisis value from its value at all subsequent crisis periods. The "DID" is the traditional differences-in-differences estimator. In this case, DID is the cross-sectional difference of time-series changes, which is computed by subtracting the average value of the time-series change of NCDF from the corresponding value of CDF (or any subgroup of CDF). P-values are reported below DID, by using Wilcoxon one-way sample t-test. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	NCDF	CDF	SBPD	SB	WBPD	WB	PDD
			{strong bank dependent firms}		{weak bank dependent firms}		
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: First year (2007Q3-2008Q2) versus Pre-crisis (2006Q3-2007Q2)							
Time-series changes	-0.8236	-1.3939	-1.7758	-1.8987	-1.5723	-1.0237	-0.5351
DID (model (2)-(7) versus NCDF)		-0.5702 ***	-0.9522 ***	-1.0751 ***	-0.7487 ***	-0.2001 **	0.2886 *
P-value		(<0.0001)	(<0.0001)	(<0.0001)	(0.0003)	(0.0375)	(0.0545)
Number of observations	906	1885	543	277	254	622	189
Panel B: Pre-Lehman (2008Q3) versus Pre-crisis (2006Q3-2007Q2)							
Time-series changes	-3.2198	-3.8272	-4.4096	-4.0529	-4.0721	-3.4381	-2.5170
DID (model (2)-(7) versus NCDF)		-0.6074 ***	-1.1898 ***	-0.8331 ***	-0.8523 ***	-0.2183	0.7028 **
P-value		(<0.0001)	(<0.0001)	(0.0023)	(<0.0001)	(0.1714)	(0.0279)
Number of observations	738	1681	518	249	223	535	156
Panel C: Post-Lehman (2008Q4-2009Q1) versus Pre-crisis (2006Q3-2007Q2)							
Time-series changes	-5.5677	-6.7279	-7.5508	-6.5896	-7.0787	-6.3535	-4.9872
DID (model (2)-(7) versus NCDF)		-1.1602 ***	-1.9831 ***	-1.0220 ***	-1.5111 ***	-0.7858 ***	0.5804
P-value		(<0.0001)	(<0.0001)	(0.0001)	(<0.0001)	(0.0006)	(0.1168)
Number of observations	724	1665	515	242	215	542	151
Panel D: Last year (2009Q2-2010Q1) versus Pre-crisis (2006Q3-2007Q2)							
Time-series changes	-3.9309	-4.7205	-5.4452	-4.6827	-4.8748	-4.4938	-2.9674
DID (model (2)-(7) versus NCDF)		-0.7896 ***	-1.5143 ***	-0.7517 **	-0.9439 ***	-0.5629 **	0.9635 ***
P-value		(<0.0001)	(<0.0001)	(0.0147)	(<0.0001)	(0.0178)	(0.0030)
Number of observations	670	1600	496	235	206	511	152

Table 8. Control Variables: Descriptive statistics.

This table reports summary statistics of the control variables used in the Propensity Score Matching method. The sample contains levered non-financial firms in the US market, found in the intersection of the CRSP and Compustat databases without missing observation on the required data. We consider a set of firm characteristics that have previously documented as determinants of default risks, including (1) Size, (2) Leverage, (3) Volatility, (4) past one year stock return (Past-ret), (5) the ratio of cash to asset (Cash/Asset), and (6) the ratio of net income to asset (NI/Cash). The Size, Leverage, Cash/Asset, and NI/Asset are computed based on the information available on 2006Q2. Volatility and Past-Ret are obtained by using the data of daily equity returns from 2005Q3 to 2006Q2. In Panel A and B, we report results for NCDF and CDF firms respectively. We also provide results across subgroups of CDF in Panel C. They are (1) SBPD when the subgroup contains rated firms with strong bank relationship; (2) SB when the subgroup contains unrated firms with strong bank relationship; (3) WBPD when the subgroup contains rated firms with weak bank relationships; (4) WB when the subgroup contains unrated firms with weak bank relationship; (5) PDD when the subgroup contains rated firms without bank.

		Size	Leverage	Volatility	Past-Ret	Cash/Asset	NI/Asset
Panel A: Non-credit-dependent firms (NCDF) (N=1069)							
	Mean	4.88	0.19	0.55	0.15	0.30	-0.03
	25th pctl	3.52	0.02	0.38	-0.22	0.09	-0.06
	Median	4.63	0.12	0.50	0.05	0.22	0.00
	75th pctl	5.95	0.29	0.67	0.37	0.47	0.02
	Std. dev.	1.77	0.21	0.24	0.54	0.25	0.08
Panel B: Credit-dependent firms (CDF) (N= 2100)							
	Mean	6.93	0.27	0.38	0.18	0.12	0.01
	25th pctl	5.71	0.13	0.26	-0.11	0.02	0.00
	Median	6.86	0.24	0.35	0.11	0.07	0.01
	75th pctl	8.11	0.37	0.45	0.36	0.16	0.02
	Std. dev.	1.89	0.20	0.17	0.46	0.14	0.04
Panel C: Subsets of the CDF							
Group 1: SBPD	Mean	8.17	0.32	0.31	0.15	0.08	0.01
Strong-Bank-Dependent	25th pctl	7.21	0.19	0.22	-0.09	0.02	0.00
and Public-Debt-Dependent firms	Median	8.01	0.28	0.29	0.09	0.05	0.01
(N=572)	75th pctl	9.09	0.41	0.37	0.29	0.11	0.03
	Std. dev.	1.38	0.19	0.13	0.38	0.09	0.03
Group 2: SB	Mean	6.27	0.23	0.38	0.18	0.08	0.01
Strong-Bank-Dependent firms	25th pctl	5.71	0.10	0.28	-0.12	0.02	0.00
(N=301)	Median	6.33	0.20	0.36	0.11	0.04	0.01
	75th pctl	6.93	0.32	0.44	0.37	0.10	0.02
	Std. dev.	1.01	0.17	0.13	0.44	0.09	0.03
Group 3: WBPD	Mean	7.70	0.33	0.35	0.19	0.11	0.00
Weak-Bank-Dependent	25th pctl	6.77	0.18	0.26	-0.10	0.03	0.00
and Public-Debt-Dependent firms	Median	7.51	0.30	0.33	0.11	0.07	0.01
(N=281)	75th pctl	8.55	0.44	0.42	0.35	0.17	0.02
	Std. dev.	1.38	0.20	0.15	0.47	0.12	0.05
Group 4: WB	Mean	5.39	0.20	0.47	0.18	0.17	0.00
Weak-Bank-Dependent firms	25th pctl	4.47	0.04	0.33	-0.17	0.03	-0.01
(N=730)	Median	5.40	0.16	0.42	0.08	0.10	0.01
	75th pctl	6.39	0.29	0.55	0.39	0.24	0.02
	Std. dev.	1.37	0.19	0.20	0.54	0.19	0.05
Group 5: PDD	Mean	8.77	0.29	0.33	0.27	0.12	0.02
Public-Debt-Dependent firms	25th pctl	7.59	0.17	0.24	0.01	0.05	0.01
(N=216)	Median	8.77	0.27	0.32	0.19	0.09	0.02
	75th pctl	9.95	0.38	0.38	0.47	0.16	0.03
	Std. dev.	1.60	0.17	0.11	0.42	0.11	0.03

Table 9. Matching estimation results.

The following table presents the results of a probit regression with identification to CDF group (or any subgroup of CDF) as the dependent variable. In Panel A, we use the full sample of firms in the intersection of CRSP-Compustat databases with non-missing observations on the required data, having non-zero leverage. In Panel B, we use Propensity Score Matching methods to find two matched groups along with similar scope on seven dimensions (Size, Leverage, Volatility, Past-Ret, Cash/Asset, NI/Asset, and Fama-French 38 industry classification) which are selected due to their importance in determining firms' default risks. P-values are reported in brackets. Pseudo-R^2 and the number of observations are reported in the last two rows.

	CDF	SBPD	SB	WBPD	WB	PDD
Model	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: the estimation results on the full sample						
Size	0.2643 ***	0.5443 ***	0.1593 ***	0.4721 ***	0.0633 **	0.5471 ***
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0115)	(<.0001)
Leverage	0.6214 ***	1.8620 ***	0.0044	1.7765 ***	0.1042	1.4028 ***
	(<.0001)	(<.0001)	(0.9882)	(<.0001)	(0.5521)	(0.0002)
Volatility	-0.5748 ***	-1.1383 ***	-1.5979 ***	-0.6584 *	-0.5203 ***	-0.2204
	(0.0007)	(0.0039)	(<.0001)	(0.0899)	(0.0050)	(0.6772)
Past-Ret	0.0322	0.1908	0.0757	0.0644	0.0150	0.2144
	(0.5590)	(0.1330)	(0.4847)	(0.5939)	(0.8104)	(0.1563)
Cash/Asset	-1.9995 ***	-3.8729 ***	-4.4760 ***	-1.8242 ***	-1.5624 ***	-1.5756 ***
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0006)
NI/Asset	1.3062 **	2.1482	3.8475 ***	-0.1125	1.6066 ***	2.6526
	(0.0138)	(0.1283)	(0.0055)	(0.9215)	(0.0048)	(0.1470)
constant	-0.1949	-2.5744 **	0.7519	-2.5867 **	-4.1877	-3.7322 ***
	(0.7793)	(0.0497)	(0.4459)	(0.0292)	(0.9741)	(0.0096)
Fixed effects	FF industry	FF industry	FF industry	FF industry	FF industry	FF industry
Peseudo-R^2	0.2948	0.6136	0.3611	0.4609	0.1211	0.5599
N	3169	1641	1370	1350	1799	1285
Panel B: the estimation results on the matched sample						
Size	-0.0122	0.0244	-0.0067	-0.0406	-0.0118	-0.0846
	(0.6520)	(0.6845)	(0.8913)	(0.5308)	(0.6921)	(0.3093)
Leverage	0.2442	-0.2328	-0.0756	-0.0349	-0.0485	-0.9865 *
	(0.2053)	(0.6100)	(0.8425)	(0.9298)	(0.8196)	(0.0935)
Volatility	0.0442	0.8758	-0.0662	0.2716	0.1324	0.4517
	(0.8405)	(0.1611)	(0.8920)	(0.6395)	(0.5740)	(0.6169)
Past-Ret	0.0028	0.0030	0.0295	-0.1343	-0.0477	-0.0408
	(0.9694)	(0.9889)	(0.8479)	(0.4703)	(0.5276)	(0.8600)
Cash/Asset	0.1664	0.6863	-0.0201	0.2876	-0.1033	-0.4429
	(0.4247)	(0.3670)	(0.9776)	(0.6299)	(0.6334)	(0.5735)
NI/Asset	0.4836	-0.5082	0.9797	-0.5935	0.5350	1.7148
	(0.4893)	(0.8165)	(0.6378)	(0.7353)	(0.4789)	(0.5531)
constant	-4.8726	-0.3408	0.1027	0.2880	0.0281	6.0029
	(0.9807)	(0.5645)	(0.8128)	(0.6512)	(0.9110)	(0.9852)
Fixed effects	FF industry	FF industry	FF industry	FF industry	FF industry	FF industry
Peseudo-R^2	0.0120	0.0384	0.0120	0.0408	0.0082	0.0521
N	1246	326	418	346	1094	230

Table 10. Matched sample analysis on default risk indicators.

The table shows matched sample analysis on default risk indicators. The matched sample is constructed by implementing Propensity Score Matching (PSM) method. In PSM, treated firms could be CDF or any subgroup within CDF (SBPD, SB, WBPD, WB, or PDD). Control firms are a subset of NCDF firms selected as the closest match to the treated firms based on the following set of firm characteristics: size, leverage, volatility of equity returns, past one year return, the ratio of cash to asset, and the ratio of net income to asset, and industry indicator variable (Fama-French 38 industry classifications). The number of observations is the number of observations on treated firms plus the number of observations on control firms. P-values are obtained by using Wilcoxon one-way sample t-test.***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. On testing bank supply shock theory and credit supply shock theory. Column 5 and 6, and Column 7 and 8 are designed to test substitution effect.

Treated firms	CDF	Strong bank dependent firms (SB+SBPD)	Weak bank dependent firms (WB+WBPD)	PDD	SBPD	SB	WBPD	WB
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: First year (2007Q3-2008Q2) versus Pre-crisis (2006Q3-2007Q2)								
Treated firms								
First year	7.1097	6.3846	7.0153	5.4076	6.5149	6.8384	6.1274	7.1713
Time-series changes	-0.8239	-1.6859	-0.933	-0.4899	-1.4685	-1.8357	-1.2701	-0.8883
Control firms (NCDF)								
First year	6.5715	6.305	6.5861	5.0964	5.3749	6.4158	5.1478	6.7078
Time-series changes	-0.8511	-0.9433	-0.898	-0.6492	-0.6694	-0.8641	-0.7474	-0.9195
DID	0.0272	-0.7426 **	-0.035	0.1593	-0.7991 **	-0.9716 **	-0.5228	0.0311
P-value	(0.4074)	(0.0277)	(0.2242)	(0.4373)	(0.0294)	(0.0258)	(0.1297)	(0.3871)
Number of observations	1059	483	993	206	290	370	305	921
Panel B: Post-Lehman (2008Q4-2009Q1)versus Pre-crisis (2006Q3-2007Q2)								
Treated firms								
Post-Lehman	1.9076	2.0482	1.8907	1.1452	1.2356	2.0814	1.2318	1.9944
Time-series changes	-6.3184	-6.8463	-6.3109	-4.9874	-6.7897	-6.6691	-6.6235	-6.2229
Control firms (NCDF)								
Post-Lehman	1.751	1.6498	1.7145	1.1134	1.2423	1.756	1.1871	1.9004
Time-series changes	-5.6164	-5.8581	-5.715	-4.5442	-5.0316	-5.7046	-4.8889	-5.6898
DID	-0.702 **	-0.9883 ***	-0.5959 **	-0.4433	-1.7581 ***	-0.9645 **	-1.7346 ***	-0.5331 *
P-value	(0.0124)	(0.0051)	(0.0305)	(0.2048)	(<0.0001)	(0.0300)	(<0.0001)	(0.0811)
Number of observations	889	423	837	177	259	323	257	779
Panel C: Last year (2009Q2-2010Q1) versus Pre-crisis (2006Q3-2007Q2)								
Treated firms								
Last year	3.9973	4.0252	4.0177	3.3119	3.1504	4.0709	3.5616	4.1376

Time-series changes	-4.5163	-5.0021	-4.4258	-2.7188	-4.9345	-4.8175	-4.3497	-4.367
Control firms (NCDF)								
Last year	3.777	3.6508	3.5311	3.1199	3.2477	3.8174	2.9193	3.7952
Time-series changes	-3.9151	-4.2184	-4.1473	-2.7621	-3.3262	-4.0808	-3.3578	-4.0781
DID	-0.6011 **	-0.7836 **	-0.2785 *	0.0434	-1.6082 ***	-0.7367 *	-0.9919 ***	-0.2889
P-value	(0.0203)	(0.0158)	(0.0861)	(0.5000)	(0.0002)	(0.0805)	(0.0061)	(0.1229)
Number of observations	833	397	793	170	240	307	239	729

Table 11. Testing the substitution effect.

The table provides the testing results on the substitution effect, which asserts that a firm's availability of switching financing resources between banks and public-debt markets is able to reduce the effect of financial crisis on its default risks. For that, we specifically choose two groups of firms, where both have strong bank relation, but only one of them is able to finance from public debt market. That is, we use DID in the pair of (SBPD and SB) or (WBPD and WB). Panel A and B are results based full sample and matched sample respectively. The matched sample is constructed by implementing Propensity Score Matching (PSM) method. In PSM, treated firms are SBPD (WBPD) and control firms are SB (WB), and are matched based on the following set of firm characteristics: size, leverage, volatility of equity returns, past one year return, the ratio of cash to asset, and the ratio of net income to asset, and industry indicator variable (Fama-French 38 industry classifications). The number of observations is the number of observations on treated firms plus the number of observations on control firms. P-values are obtained by using Wilcoxon one-way sample t-test.***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

		SBPD versus SB	**WBPD versus WB**
Time phase		(strong-bank-dependent firms)	(weak-bank-dependent firms)
Panel A: full sample			
First-year crisis	**DID**	0.1228	-0.5486 **
	P-value	(0.4447	(0.0243
	Number of observations	820	876
Pre-Lehman	**DID**	-0.3567 **	-0.634 ***
	P-value	(0.0275)	(0.0007)
	Number of observations	767	758
Post-Lehman	**DID**	-0.9612 ***	-0.7252 ***
	P-value	(0.0001)	(<0.0001)
	Number of observations	757	757
Last-year crisis	**DID**	-0.7626 ***	-0.381 ***
	P-value	(0.0008)	(0.0070)
	Number of observations	731	717
Panel B: matched sample			
First-year crisis	**DID**	-0.2449	-0.1728
	P-value	(0.2517)	(0.4946)
	Number of observations	234	234
Pre-Lehman	**DID**	-0.0846	-0.0143
	P-value	(0.2465)	(0.3841)
	Number of observations	224	196
Post-Lehman	**DID**	0.1004	-0.4705 *
	P-value	(0.4011)	(0.0612)

	Number of observations	224	194
Last-year crisis	**DID**	-0.2172	-0.7059 *
	P-value	(0.2621)	(0.0564)
	Number of observations	217	190

Table 12. Summary Statistics

The summary statistics are for a sample of 45,565 firm-year observations from 1986 to 2011. Firms are identified either bank dependent (BD) or public debt dependent (PDD). BD firms are unrated firms and PDD firms are rated firm, where the rating information is extracted from COMPUSTAT with item SPLTICRM. The subsample that only contains BD (PDD) firms has 27,122 (18,443) firm-year observations. Interquartile is the difference between first and third quartiles. EDF is expected default probability and DD is distance-to-default, and they are measured based on Merton's model. *LT-1t-1* is defined as the amount of the firm *i*'s long-term debt outstanding at the end of year *t-1* that is due for repayment in year t (i.e., COMPUSTAT item *dd1* in year *t-1*) scaled by the current book value of total assets. We control for many relevant default risk factors in our default risk regression. They are: *Cash*, *Market to book*, *Idiovol*, *Tangibility*, *Size*, *R&D*, *Tax*, *Profitability*, *Leverage*, and *Interest coverage*. Details on the definition of these variables are provided in the Appendix B. The statistically significant differences between the characteristics of rated and nonrated firms are marked *** for 1% level.

	Full sample				Bank dependent firms (BD firms)		Public debt dependent firms (PDD firms)		
Variable	Mean	Median	S.D.	Interquartile range	Mean	Median	Mean	Median	Diff. of Mean of BD and PDD
EDF	0.105	0.001	0.216	0.079	0.124	0.003	0.076	0	0.048 ***
DD	4.821	4.251	3.956	5.029	4.119	3.54	5.854	5.358	-1.734 ***
LT-1$_{t-1}$	0.028	0.011	0.087	0.026	0.035	0.014	0.018	0.007	0.017 ***
Cash	0.088	0.045	0.115	0.1	0.096	0.046	0.077	0.044	0.019 ***
Market to book	1.301	0.961	1.178	0.827	1.329	0.937	1.261	0.996	0.069 ***
Idiovol	0.037	0.028	0.028	0.025	0.044	0.035	0.026	0.021	0.018 ***
Tangibility	0.354	0.305	0.234	0.348	0.341	0.29	0.374	0.331	-0.033 ***
Size	6.038	6.045	2.232	3.167	4.823	4.817	7.825	7.729	-3.002 ***
R&D	0.022	0	0.051	0.021	0.027	0	0.015	0	0.012 ***
Tax	0.019	0.015	0.028	0.034	0.017	0.012	0.021	0.019	-0.004 ***
Profitability	-0.015	0.066	0.661	0.098	-0.083	0.05	0.086	0.09	-0.169 ***
Leverage	0.33	0.298	0.191	0.237	0.312	0.278	0.357	0.322	-0.045 ***
Interest coverage	5.36	3.861	11.602	5.723	4.598	3.479	6.481	4.347	-1.883 ***

Table 13. Correlation matrix

The correlations are for a sample of 45,565 Compustat firm-year observations from 1986 to 2011. EDF is expected default probability and DD is distance-to-default, and they are measured based on Merton's model. *LT-1t-1* is defined as the amount of the firm *i*'s long-term debt outstanding at the end of year *t-1* that is due for repayment in year t (i.e., COMPUSTAT item *dd1* in year *t-1*) scaled by the current book value of total assets. Other default risk factors used our default risk regression are: *Cash*, *Market to book*, *Idiovol*, *Tangibility*, *Size*, *R&D*, *Tax*, *Profitability*, *Leverage*, and *Interest coverage*. The detail construction of these variables is provided in Appendix B. * Indicates correlation is significantly different from zero at the 0.05 level or higher.

	EDF	*DD*	*LT-1t-1*	*Cash*	*Market to book*	*Idiovol*	*Tangibility*	*Size*	*R&D*	*Tax*	*Profitability*	*Leverage*
DD	-0.61*											
LT-1t-1	0.19*	-0.15*										
Cash	-0.04*	0.05*	-0.01									
Market to book	-0.21*	0.33*	0.04*	0.23*								
Idiovol	0.68*	-0.62*	0.18*	0.02*	-0.05*							
Tangibility	-0.01*	0	0	-0.25*	-0.08*	-0.05*						
Size	-0.18*	0.36*	-0.13*	-0.07*	-0.12*	-0.54*	0.10*					
R&D	-0.01	-0.01*	0.02*	0.41*	0.31*	0.12*	-0.24*	-0.15*				
Tax	-0.27*	0.42*	-0.08*	0.01*	0.20*	-0.31*	-0.03*	0.17*	-0.06*			
Profitability	-0.13*	0.14*	-0.08*	-0.26*	-0.18*	-0.24*	0.05*	0.21*	-0.34*	0.17*		
Leverage	0.33*	-0.39*	0.16*	-0.14*	-0.01	0.23*	0.13*	-0.03*	-0.08*	-0.27*	-0.08*	
Interest coverage	-0.23*	0.39*	-0.09*	-0.03*	0.09*	-0.32*	-0.03*	0.25*	-0.18*	0.49*	0.37*	-0.27*

Table 14. Rollover risk effect on default risk

This table reports the results of regressions aimed at understanding rollover risk effect on default probability. The dependent variable is ΔEDF, the year-on-year change in expected default frequency measured based on Merton's model. The main independent variable is ΔLT-1t-1, the year-on-year change in long-term debt outstanding at the end of year t-1 that is due repayment in year t. Column 3 and 4 present results of rollover risk effect on default risk dependent on financial sources (being bank dependent firms or not). BD_dummy is zero-one dummy variable, where it equals to one if the firm is identified as a BD firm, otherwise 0. We control for many relevant default risk factors in our default risk regression. They are: Cash, Market to book, Idiovol, Tangibility, Size, R&D, Tax, Profitability, Leverage, and Interest coverage. Details on the definition of these variables are provided in the Appendix B. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

	Effect of ΔLT-1t-1 on ΔEDF			
	(1)	(2)	(3)	(4)
ΔLT-1t-1	0.067 ***	0.081 ***		
	(0.022)	(0.019)		
ΔLT-1t-1 x BD_dummy			0.066 ***	0.078 ***
			(0.023)	(0.019)
ΔLT-1t-1 x (1-BD_dummy)			0.075	0.119 *
			(0.061)	(0.062)
ΔCash		-0.025 *		-0.025 *
		(0.013)		-0.013
ΔMarket to book		-0.018 ***		-0.018 ***
		(0.001)		(0.001)
ΔIdiovol		4.543 ***		4.543 ***
		(0.110)		(0.111)
ΔTangibility		0.015		0.014
		(0.016)		(0.016)
ΔSize		0.001		0.001
		(0.004)		(0.004)
ΔR&D		0.015		0.015
		(0.039)		(0.039)
ΔTax		-0.08 *		-0.081 *
	`	(0.040)		(0.040)
ΔProfitability		-0.005 **		-0.005 **
		(0.002)		(0.002)
ΔLeverage		0.148 ***		0.148 ***
		(0.011)		(0.011)
ΔInterest coverage		-0.0002 **		0 ***
		(0.000)		(0.000)
Const.	0.023 ***	-0.013 *	0.023 ***	-0.013 *
	(0.008)	(0.007)	(0.008)	(0.007)
Obs.	45371	45371	45371	45371
R2	0.077	0.295	0.077	0.295
Year FE	Yes	Yes	Yes	Yes

Table 15. Rollover risk effect on default risk conditional on credit quality, size, and recession

This table reports the results of regressions aimed at understanding whether rollover risk effect is conditional on credit quality, size, and recession. The dependent variable is ΔEDF, the year-on-year change in expected default frequency measured based on Merton's model. The main independent variable is ΔLT-1t-1, the year-on-year change in long-term debt outstanding at the end of year t-1 that is due repayment in year t. The whole sample is split into two halves based on the median value of EDF, where low-EDF (high-EDF) group is the one with good (bad) credit quality, (see Column 1 and 2), and the median value of size, where large-size group and small-size group are presented in Column 3 and 4 respectively, and during recession or not (Column 5 and 6). Panel B present results of rollover risk effect on default risk dependent on financial sources (being bank dependent firms or not). BD_dummy is zero-one dummy variable, where it equals to one if the firm is identified as a BD firm, otherwise 0. We control for many relevant default risk factors in our default risk regression. They are: Cash, Market to book, Idiovol, Tangibility, Size, R&D, Tax, Profitability, Leverage, and Interest coverage. Details on the definition of these variables are provided in the Appendix B. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

Panel A: Rollover risk conditional on credit quality, size and recession

	Credit quality		Size		Recession	
	Good	Bad	Large	Small	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLT-1t-1	0.046	0.084 ***	0.190 ***	0.069 ***	0.079 ***	0.080 ***
	(0.035)	(0.019)	(0.046)	(0.018)	(0.023)	(0.024)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	22682	22689	22738	22633	10785	34586
R2	0.088	0.347	0.223	0.365	0.309	0.275
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Across BD and PDD firms

	Credit quality		Size		Recession	
	Good	Bad	Large	Small	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLT-1t-1 x BD_dummy	0.045	0.081 ***	0.206 ***	0.070 ***	0.074 ***	0.077 ***
	(0.045)	(0.019)	(0.072)	(0.018)	(0.020)	(0.025)
ΔLT-1t-1 x (1-BD_dummy)	0.049	0.129 *	0.175 **	0.052	0.146	0.11 *
	(0.045)	(0.075)	(0.069)	(0.100)	(0.128)	(0.064)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	22682	22689	22738	22633	10785	34586
R2	0.088	0.347	0.223	0.365	0.309	0.275
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 16. Rollover risk effect on default risk measured by Distance-to-Default

This table reports the results of regressions aimed at understanding rollover risk effect on default probability. The dependent variable is ΔDD, the year-on-year change in distance-to-default measured based on Merton's model. The main independent variable is ΔLT-1t-1, the year-on-year change in long-term debt outstanding at the end of year t-1 that is due repayment in year t. Column 3 and 4 present results of rollover risk effect on default risk dependent on financial sources (being bank dependent firms or not). BD_dummy is zero-one dummy variable, where it equals to one if the firm is identified as a BD firm, otherwise 0. We control for many relevant default risk factors in our default risk regression. They are: Cash, Market to book, Idiovol, Tangibility, Size, R&D, Tax, Profitability, Leverage, and Interest coverage. Details on the definition of these variables are provided in the Appendix B. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

	Effect of ΔLT-1t-1 on ΔDD			
	(1)	(2)	(3)	(4)
ΔLT-1t-1	-0.453 **	-0.629 ***		
	(0.180)	(0.165)		
ΔLT-1t-1 x BD_dummy			-0.393 **	-0.551 ***
			(0.160)	(0.150)
ΔLT-1t-1 x (1-BD_dummy)			-1.085 *	-1.466 **
			(0.548)	(0.580)
Δ*Cash*		1.269 ***		1.262 ***
		(0.195)		(0.195)
Δ*Market to book*		0.605 ***		0.605 ***
		(0.037)		(0.037)
Δ*Idiovol*		-26.404 ***		-26.418 ***
		(0.650)		(0.658)
Δ*Tangibility*		0.063		0.067
		(0.227)		(0.227)
Δ*Size*		0.112 *		0.111 *
		(0.059)		(0.059)
Δ*R&D*		-1.279 ***		-1.281 ***
		(0.353)		(0.353)
Δ*Tax*		0.959 **		0.972
		(0.686)		(0.686)
Δ*Profitability*		0.054		0.054 *
		(0.025)		(0.025)
Δ*Leverage*		-2.787 ***		-2.79 ***
		(0.167)		(0.167)
Δ*Interest coverage*		0.008 ***		0.008 ***
		(0.002)		(0.002)
Const.	-0.94 ***	-0.644 ***	-0.94 ***	-0.643 ***
	(0.154)	(0.150)	(0.154)	(0.150)
Obs.	45371	45371	45371	45371
R2	0.257	0.346	0.257	0.346
Year FE	Yes	Yes	Yes	Yes

Table17. Rollover risk effect on distance-to-default conditional on credit quality, size, and recession

This table reports the results of regressions aimed at understanding whether rollover risk effect is conditional on credit quality, size, and recession. The dependent variable is ΔDD, the year-on-year change in distance-to-default measured based on Merton's model. The main independent variable is ΔLT-1t-1, the year-on-year change in long-term debt outstanding at the end of year t-1 that is due repayment in year t. The whole sample is split into two halves based on the median value of DD, where high-DD (low-DD) group is the one with good (bad) credit quality, (see Column 1 and 2), and the median value of size, where large-size group and small-size group are presented in Column 3 and 4 respectively, and during recession or not (Column 5 and 6). Panel B present results of rollover risk effect on default risk dependent on financial sources (being bank dependent firms or not). BD_dummy is zero-one dummy variable, where it equals to one if the firm is identified as a BD firm, otherwise 0. We control for many relevant default risk factors in our default risk regression. They are: Cash, Market to book, Idiovol, Tangibility, Size, R&D, Tax, Profitability, Leverage, and Interest coverage. Details on the definition of these variables are provided in the Appendix B. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

	Panel A: Rollover risk conditional on credit quality, size and recession					
	Credit quality		Size		Recession	
	Good	Bad	Large	Small	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLT-1t-1	-0.713	-0.617 ***	-1.721 ***	-0.521 ***	-0.850 ***	-0.574 ***
	(0.775)	(0.128)	(0.611)	(1.143)	(0.167)	(0.208)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	22698	22673	22738	22633	10785	34586
R2	0.421	0.321	0.370	0.380	0.343	0.315
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

	Panel B: Across BD and PDD firms					
	Credit quality		Size		Recession	
	Good	Bad	Large	Small	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLT-1t-1 x BD_dummy	-0.745	-0.541 ***	-1.597 ***	-0.512 ***	-0.824 ***	-0.472 **
	(1.030)	(0.116)	(0.710)	(0.133)	(0.163)	(0.185)
ΔLT-1t-1 x (1-BD_dummy)	-0.635	-1.633 ***	-1.846 **	-0.720	-1.197	-1.563 **
	(0.954)	(0.479)	(0.745)	(0.733)	(0.833)	(0.596)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	22698	22673	22738	22633	10785	34586
R2	0.421	0.321	0.370	0.380	0.343	0.315
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 18. Using rating as the proxy of default risk

This table reports the results of regressions aimed at understanding rollover risk effect on default probability. The dependent variable is Δrating, the year-on-year change in credit rating extracted from COMPUSTAT with item of "SPLTICRM". The letter ratings are transformed into numerical equivalents, using an ordinal scale that ranges from 1 for the highest-rated firms (AAA) to 22 for the lowest-rated firms (D: Default). The main independent variable is ΔLT-1t-1, the year-on-year change in long-term debt outstanding at the end of year t-1 that is due repayment in year t. Control variable are: Cash, Market to book, Idiovol, Tangibility, Size, R&D, Tax, Profitability, Leverage, and Interest coverage. Details on the definition of these variables are provided in the Appendix B. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

	(1)	(2)
ΔLT-1t-1	0.481 **	0.567 ***
	0.195	0.185
Intercept	Yes	Yes
Control Variables	No	Yes
Obs.	17540	17540
R2	0.0272	0.200
Year FE	Yes	Yes

Table 19. Rollover risk effect conditional on credit quality, size, recession.

	Effect of ΔLT-1t-1 on ΔEDF			Effect of ΔLT-1t-1 on ΔDD		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLT-1t-1 x credit_dummy	0.085 ***			-0.640 ***		
	(0.020)			(0.138)		
ΔLT-1t-1 x (1-credit_dummy)	0.044			-0.499		
	(0.039)			(0.796)		
ΔLT-1t-1 x Large		0.189 ***			-1.707 ***	
		(0.049)			(0.555)	
ΔLT-1t-1 x (1-Large)		0.070 ***			-0.514 ***	
		(0.019)			(0.151)	
ΔLT-1t-1 x Recession			0.083 ***			-0.738 ***
			(0.023)			(0.144)
ΔLT-1t-1 x (1-Recession)			0.081 ***			-0.583 ***
			(0.023)			(0.205)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	45371	45371	45371	45371	45371	45371
R2	0.2954	0.2957	0.295	0.346	0.3464	0.346
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 20. Rollover risk effect conditional on credit quality, size, recession with tercile identification and using EDF as proxy for default risk.

Dependent variable is ΔEDF. Unlike the main analysis of which using sample median value to identify firms' type, we sort firms into terciles based on their EDF and size. We consider firms included in the first tercile as those with good credit quality and small size, and firms included in the third tercile as those with bad credit quality and large size.

	Panel A: Rollover risk conditional on credit quality, size and recession			
	Credit quality		Size	
	Good	Bad	Large	Small
	(1)	(2)	(3)	(4)
ΔLT-1t-1	0.111 *	0.080 ***	0.329 ***	0.054 ***
	(0.062)	(0.018)	(0.084)	(0.017)
Control variables	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Obs.	15120	15114	15164	15081
R2	0.038	0.372	0.185	0.377
Year FE	Yes	Yes	Yes	Yes
	Panel B: Across BD and PDD firms			
	Credit quality		Size	
	Good	Bad	Large	Small
	(1)	(2)	(3)	(4)
ΔLT-1t-1 x BD_dummy	0.132	0.079 ***	0.640 ***	0.054 ***
	(0.091)	(0.018)	(0.125)	(0.017)
ΔLT-1t-1 x (1-BD_dummy)	0.076	0.089	0.235 **	0.031
	(0.060)	0.085	(0.095)	(0.114)
Control variables	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Obs.	15120	15114	15164	15081
R2	0.039	0.372	0.186	0.377
Year FE	Yes	Yes	Yes	Yes

Table 21. Rollover risk effect conditional on credit quality, size, recession with tercile identification and using DD as proxy for default risk.

Dependent variable is ΔEDF. Unlike the main analysis of which using sample median value to identify firms' type, we sort firms into terciles based on their DD and size. We consider firms included in the first tercile as those with bad credit quality and small size, and firms included in the third tercile as those with good credit quality and large size.

	Panel A: Rollover risk conditional on credit quality, size and recession			
	Credit quality		Size	
	Good	Bad	Large	Small
	(1)	(2)	(3)	(4)
ΔLT-1t-1	-1.942	-0.577 ***	-3.056 **	-0.390 ***
	(1.278)	(0.117)	(1.210)	(0.126)
Control variables	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Obs.	15131	15107	15164	15081
R2	0.447	0.295	0.363	0.379
Year FE	Yes	Yes	Yes	Yes

	Panel B: Across BD and PDD firms			
	Credit quality		Size	
	Good	Bad	Large	Small
	(1)	(2)	(3)	(4)
ΔLT-1t-1 x BD_dummy	-1.990	-0.526 ***	-5.514 ***	-0.389 ***
	(1.917)	(0.114)	(1.905)	(0.118)
ΔLT-1t-1 x (1-BD_dummy)	-1.868	-1.376 ***	-2.312 **	-0.477
	(1.183)	(0.439)	(1.097)	(1.114)
Control variables	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Obs.	15131	15107	15164	15081
R2	0.447	0.295	0.363	0.379
Year FE	Yes	Yes	Yes	Yes

Table 22. Rollover risk effect conditional on credit quality, size, recession with quartile identification and using EDF as proxy for default risk.

Dependent variable is ΔEDF. Unlike the main analysis of which using sample median value to identify firms' type, we sort firms into quartiles based on their EDF and size. We consider firms included in the first quartile as those with good credit quality and small size, and firms included in the third quartile as those with bad credit quality and large size.

	Panel A: Rollover risk conditional on credit quality, size and recession			
	Credit quality		Size	
	Good	Bad	Large	Small
	(1)	(2)	(3)	(4)
ΔLT-1t-1	0.153	0.074 ***	0.345 ***	0.049 ***
	(0.096)	(0.019)	(0.081)	(0.017)
Control variables	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Obs.	11340	11338	11376	11301
R2	0.037	0.380	0.158	0.384
Year FE	Yes	Yes	Yes	Yes

	Panel B: Across BD and PDD firms			
	Credit quality		Size	
	Good	Bad	Large	Small
	(1)	(2)	(3)	(4)
ΔLT-1t-1 x BD_dummy	0.203	0.073 ***	1.065 ***	0.049 ***
	(0.153)	(0.018)	(0.186)	(0.017)
ΔLT-1t-1 x (1-BD_dummy)	0.091	0.088	0.175 **	0.090
	(0.076)	(0.096)	(0.082)	(0.100)
Control variables	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Obs.	11340	11338	11376	11301
R2	0.039	0.380	0.161	0.384
Year FE	Yes	Yes	Yes	Yes

Table 23. Rollover risk effect conditional on credit quality, size, recession with quartile identification and using DD as proxy for default risk.

Dependent variable is ΔEDF. Unlike the main analysis of which using sample median value to identify firms' type, we sort firms into terciles based on their DD and size. We consider firms included in the first tercile as those with bad credit quality and small size, and firms included in the third tercile as those with good credit quality and large size.

	Panel A: Rollover risk conditional on credit quality, size and recession			
	Credit quality		Size	
	Good	Bad	Large	Small
	(1)	(2)	(3)	(4)
ΔLT-1t-1	-2.276	-0.566 ***	-4.406 ***	-0.354 ***
	(1.589)	(0.117)	(1.383)	(0.130)
Control variables	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Obs.	11349	11325	11376	11301
R2	0.463	0.275	0.355	0.379
Year FE	Yes	Yes	Yes	Yes

	Panel B: Across BD and PDD firms			
	Credit quality		Size	
	Good	Bad	Large	Small
	(1)	(2)	(3)	(4)
ΔLT-1t-1 x BD_dummy	-2.245	-0.511 ***	-10.346 ***	-0.351 ***
	(2.493)	(0.111)	(3.029)	(0.122)
ΔLT-1t-1 x (1-BD_dummy)	-2.317	-1.525 ***	-3.002 **	-0.692
	(1.458)	(0.528)	(1.382)	(1.686)
Control variables	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Obs.	11349	11325	11376	11301
R2	0.463	0.275	0.355	0.379
Year FE	Yes	Yes	Yes	Yes

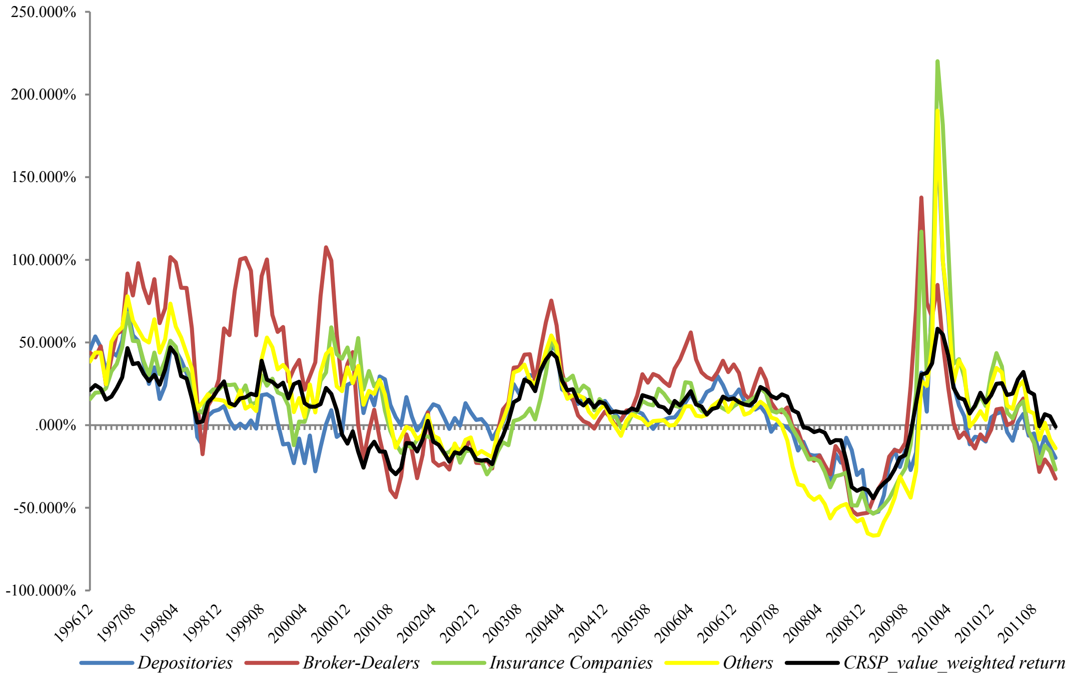


Figure 1. Annual equity returns by sector.

This figure presents the annual equity returns, calculated by summing daily returns over the past year at the end of every month, spanned December 1996 to December 2011 for each sector. The sector-level annual return ending at month t for sector k is calculated by $r_{k,t} = \sum_{j=1}^{10} w_{j,k,t} \times r_{j,k,t}$, where $r_{j,k,t}$ is firm j's annual return, and $w_{j,k,t}$ is the weight, based on the market equity of firm j at the end of month t. The blue, red, green, and yellow lines represent Depositories, Broker-Dealers, Insurance Companies, and Others respectively. The black line represents the annual return on CRSP value-weighted index.

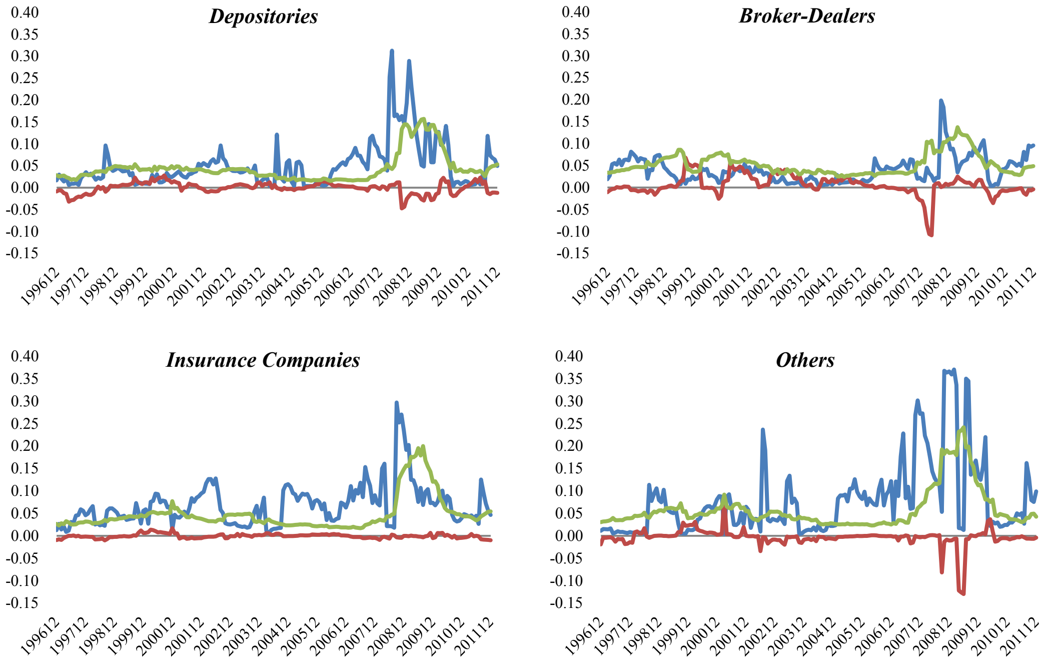
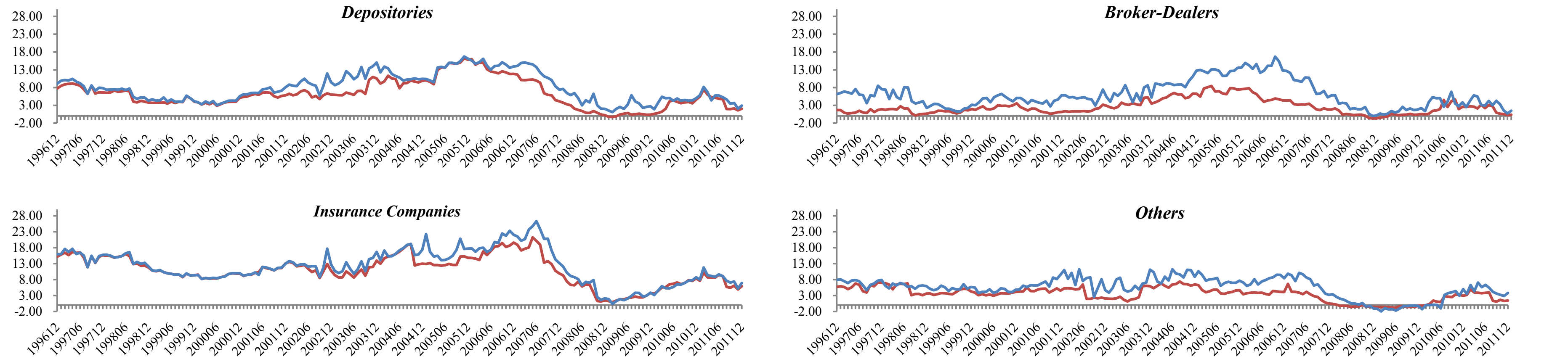
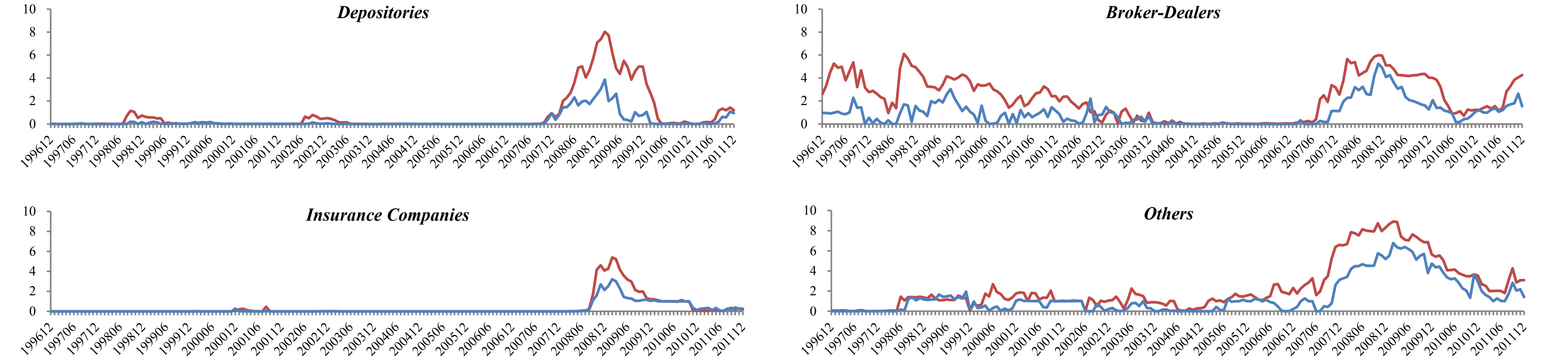


Figure 2. Jump process parameters.

The figure presents the three time series obtained from the estimation of correlated jumps in each sector. The results are plotted at the end of each rolling window sample, with 181 monthly observations for each time series. The blue, red, and green lines represent λ (intensity of correlated jumps), *mu_coj* (average value of the means of jump size for 10 big financial institutions), and *std_coj* (average value of standard deviations of jump size for 10 big financial institutions), respectively.



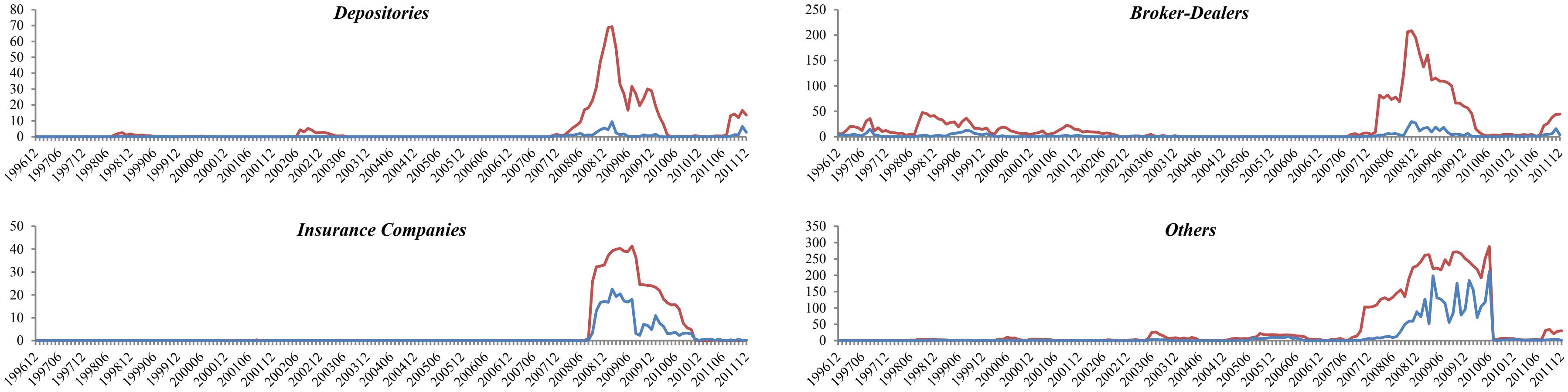
Panel A: *DD*



Panel B: *NoD*

Figure 3. Systemic risk measures.

This figure presents three alternative systemic risk measures, *DD* (distance-to-default, Panel A), *NoD* (number of joint defaults, Panel B), and *PIR* (price of insurance ratio, Panel C) during 1996–2011 by sector. The red and blue lines represent measures derived from our model and the benchmark, respectively.. (Conti.



Panel C: *PIR*

Figure 3 (Conti.). Systemic risk measures.

This figure presents an alternative systemic risk measure, *PIR*, during 1996-2011, by sector. The *PIR* (Panel C) is the ratio of the price of insurance against financial distress to the aggregate asset value (scaled by multiplying 10^6).

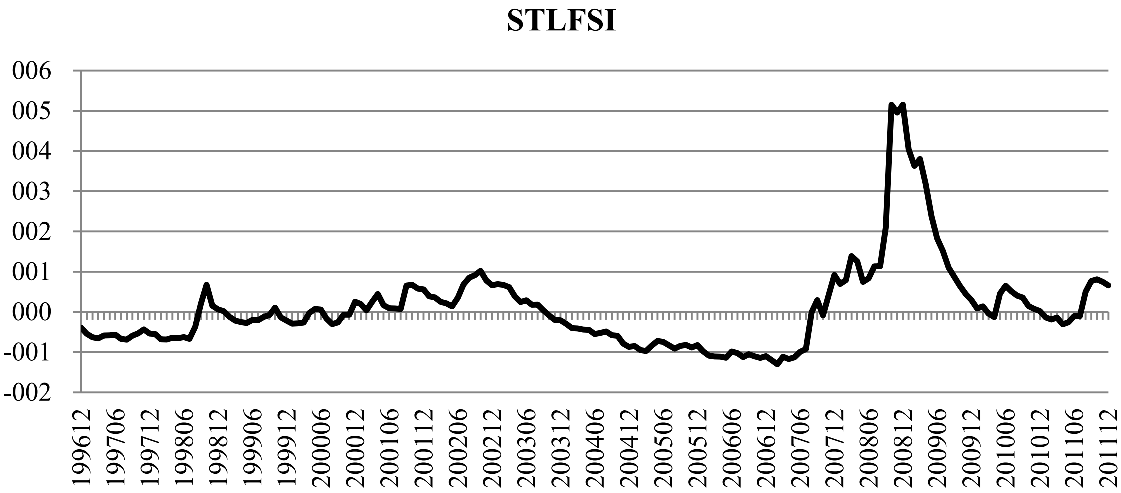
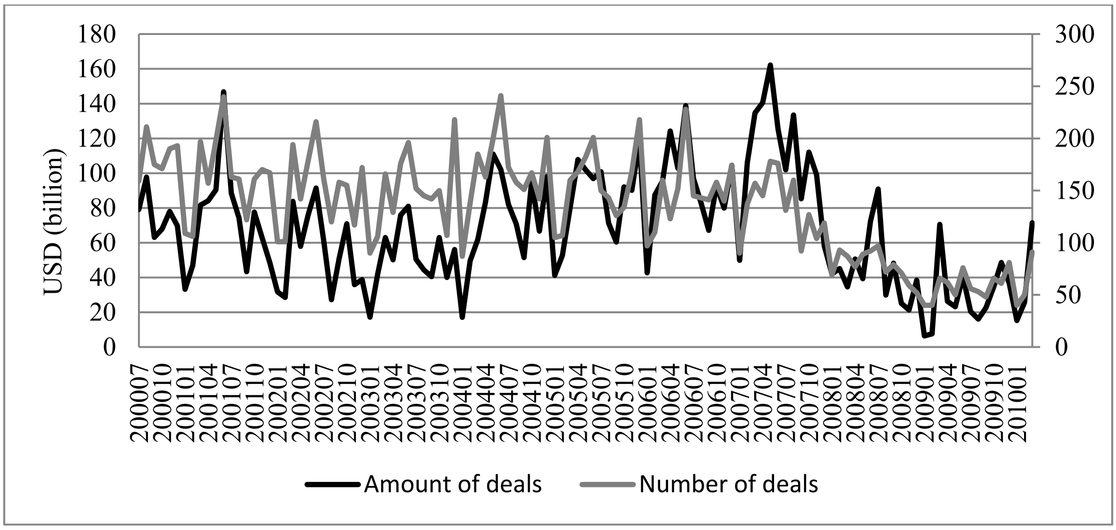
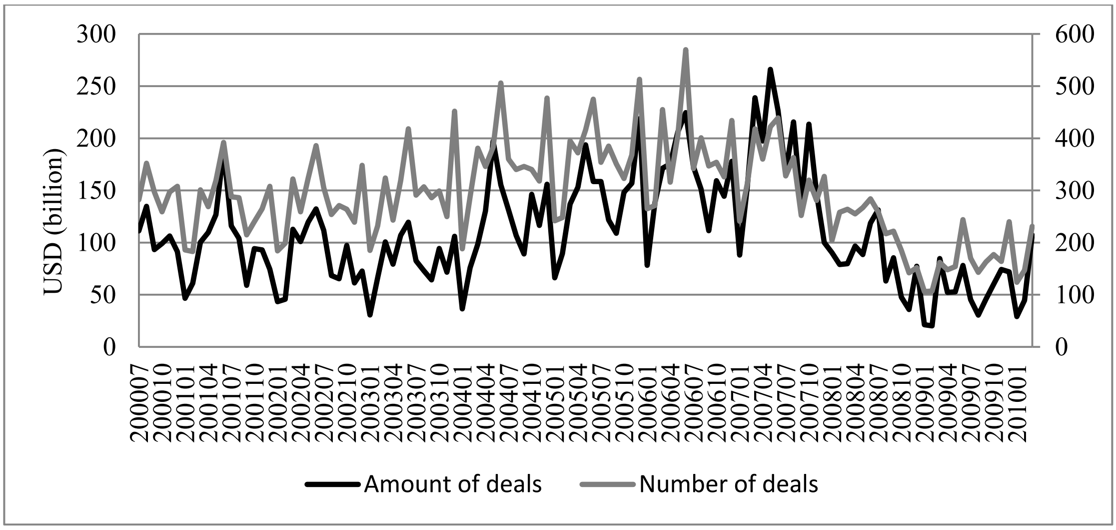


Figure 4. St. Louis Fed Financial Stress Index (STLFSI).
This figure presents monthly data of STLFSI, from December 1996 to December 2011.



Panel A: Public firms



Panel B: All firms

Figure 5. Bank loans from 2000Q3 to 2010Q1.

This figure shows the total amount (the left-axis) and number (the right-axis) of new bank loans issues for each month over the period of 2003Q3−2010Q1. The black and gray lines represent the total amount of deals and the total number of deals for a given month respectively. Panel A reports the profile of bank loans for firms that are public and listed in Compustat database and Panel B shows it for all firms.

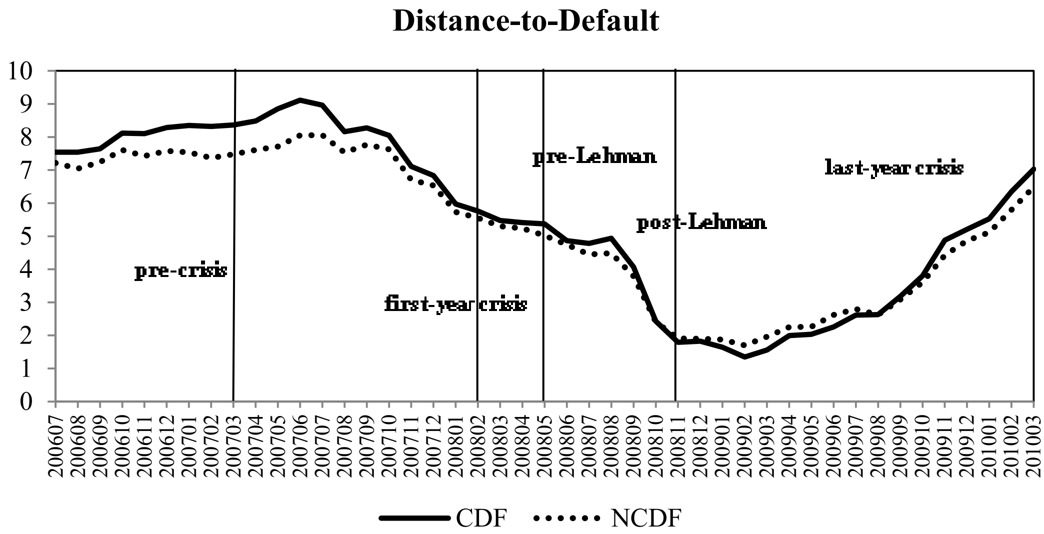
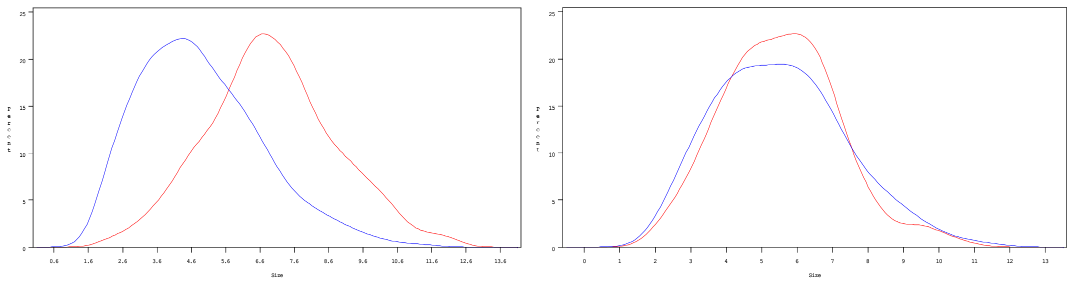
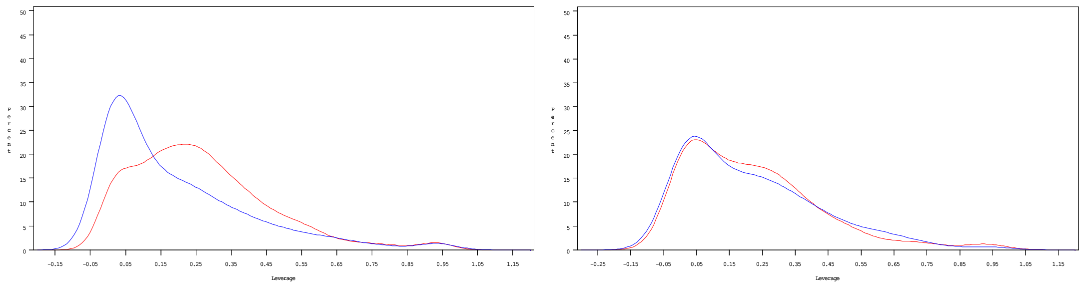


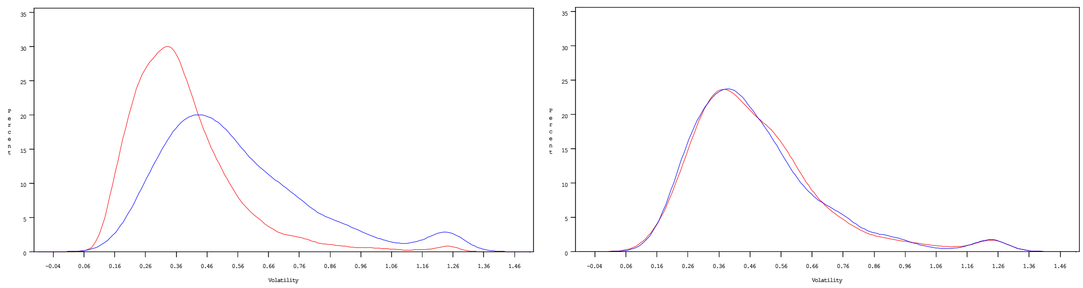
Figure 6. Distance-to-Default from 2006Q2 to 2010Q1.
This figure shows the movements over time of distance-to-default for groups of CDF (solid line) and of NCDF (dotted line). The vertical lines separate five crisis periods.



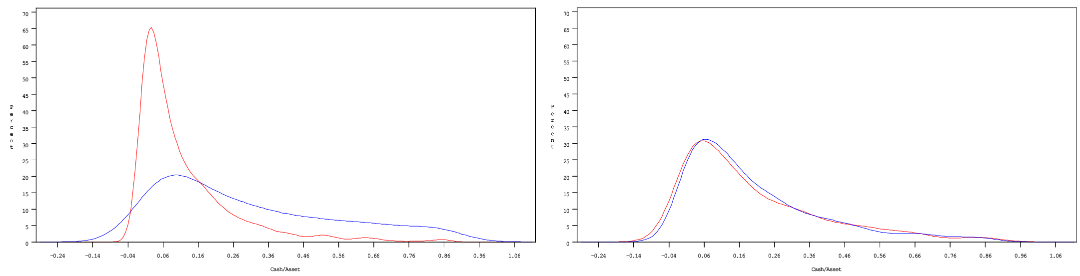
Panel A: Size



Panel B: Leverage



Panel C: Volatility



Panel D: Cash/Asset

Figure 7. Distributions of key characteristics on firms' defaults.

The diagrams plot the kernel density functions of key characteristics related to firms' default. Distribution for the entire sample (pre-match) is presented in the left-hand side and distribution for the matched sample is presented in the right-hand side. Distributions of Size, Leverage, Volatility, and Cash/Asset are displayed in Panel A, B, C, and D respectively. The red (blue) line represents firms that have higher (lower) and lower dependence on external financing firms (CDF versus NCDF).